The Safety Net as a Springboard? A General Equilibrium based Policy Evaluation*

Domenico Ferraro
Arizona State University

Nir Jaimovich
University of Zurich and *CEPR*

Francesca Molinari
Cornell University

Cristobal Young
Cornell University

August 2020

Abstract

We develop a search-and-matching model where the magnitude of unemployment insurance benefits affects the likelihood that unemployed actually engage in active job search. To quantitively discipline this relation we use administrative data of unemployed search audits. We use the model to quantify the effects of unemployment reforms. For small benefits' increases, the policymaker faces a trade-off between an uptick in the measure of unemployed actually searching and a fall in the unemployment exit-rate conditional on searching. For larger benefits' increases, an active search margin magnifies the benefits' disincentives, leading to a bigger drop in the employment rate than previously thought.

JEL Classification: E24; J64; J65.

Keywords: Unemployment insurance; Search behavior; Costly search; Liquidity effect.

*We thank Gadi Barlevy, Giacomo De Giorgi, Bart Hobijn, Zhuan Pei, Ofer Setty, Henry Siu, Nicolas Vincent, and numerous seminar audiences for helpful comments. All remaining errors are our own.

1. Introduction

We develop a general equilibrium search-and-matching model where the magnitude of unemployment insurance benefits affects the likelihood that unemployed individuals actually engage in active job search. With the aid of our quantitative model, we uncover novel implications of the effect of unemployment insurance reforms on employment rates; our model shows that the relation between benefit changes and employment rates could, in fact, be positive, or even more negative than what was previously thought – as we discuss below, the exact impact on the employment rate depends on the magnitude of the reforms.

Although job search is central to models of unemployment, and typically a prerequisite for the collection of benefits, evidence on its relation to unemployment benefits generosity is scant. As such, to quantitively discipline the relation between unemployment insurance benefits and the likelihood of search we use an administrative dataset featuring records from *random audits* verifying whether benefit recipients engaged in active job search (in violation of state requirements, a nontrivial fraction of these individuals do not actively look for a job), alongside information about the (i) amount of collected benefits, (ii) previous wages and (iii) various demographic and labor market variables. Our estimation approach capitalizes on the fact that in several U.S. states the amount of unemployment benefits partially rely on a random timing criteria; as the Department of Labor and Administration (2005) notes, "*depending on the distribution of wages in the base period, workers with the same total base period wages can have... different weekly benefit amounts.*" Our estimates suggest that more generous unemployment insurance benefits make it likelier that an individual will undertake a job search for most deciles of the wage distribution.

To formally model the channel via which unemployment benefits affect the search likelihood we build on the important literature that underscores the impact of liquidity constraints on the unemployed (e.g., Chetty, 2008), as well as the influential literature highlighting the liquidity constraints of hand-to-mouth individuals (e.g. Jappelli (1990), Jappelli and Pistaferri (2010), Kaplan and Violante (2014), Kaplan, Violante and Weidner (2014), Jappelli and Pistaferri (2014)). Indeed, via the lens of a simple partial-equilibrium model of endogenous job search, we identify "monetary search costs" as an important, yet overlooked, mechanism through which unemployment benefits affect job search of hand-to-mouth individuals.[1] Then, to quantitatively evaluate policy

[1]Examples of such costs include those for "presentation of self" (clothing and personal grooming), transportation, home computer and internet access, resumé service or employment agency fees, and child care. In fact, the U.S. tax code specifically permits deductions of various items related to job search, thus recognizing the importance of such

reforms, we develop a structural search-and-matching, heterogeneous-agent, general equilibrium model where risk-averse unemployed individuals optimally decide whether to search for work, a process which entails a monetary cost. We employ indirect inference methods where our novel empirical estimates discussed above are used as identified moments the model matches.

We then use the model to evaluate the impact of reforms in the magnitude of unemployment benefits.[2] Overall, we find that "small" reforms with a limited increase in benefits (in a manner made precise in our modelling section) result in an increase in the measure of job searchers. This increase mitigates the negative impact of the decline in the probability of finding a job on employment rates, and in fact, depending on the exact wage mechanism we consider, can raise the employment rate. Hence, for such small reforms there is a trade-off resulting from higher benefits. On one hand, higher benefits raise the likelihood of search, as our empirical results indicate. On the other hand, they have a disincentive effect as they reduce the job-finding rate conditional on searching.

However, for larger reforms we find a reduction in the search likelihood which magnifies the fall in employment rates. Importantly, this sign flip in the search likelihood is fully consistent with our estimates of a positive elasticity of the likelihood of engaging in active search. In the model, this sign flip is due to general equilibrium effects that operate through the reduction in the job-finding probability conditional on searching, which cannot be captured by the reduced-form estimates in our empirical analysis.

The paper proceeds as follows. Section 2 presents our data, discusses the empirical approach, and presents the empirical results regarding the relation between job search and unemployment insurance benefits. We then rationalize these results with a simple non-parametric partial-equilibrium model presented in Section 3. Based on the insights from this model, we build our general-equilibrium quantitative model in Section 4. We discuss the general-equilibrium model's parametrization in Section 5, and consider its policy implications in Section 6. Finally, Section 7 concludes the paper. The different appendices contain various robustness checks that pertain to the empirical and theoretical analysis.

monetary search costs. Moreover, Phillips (2014), studies a randomized experiment that provided a transportation subsidy package to low-wage job seekers in Washington, DC, finding evidence that search costs matter to the urban poor. Similarly, Franklin (2018) shows in a randomized trial in Ethiopia that cash constraints lead young individuals to give up looking for jobs.

[2] It is important to stress that the estimated reduced-form elasticities discussed above are not "structural" parameters and cannot be readily used for policy analysis. Additionally, the reduced form estimates cannot take into account the effects of the changes in taxes required to finance the reform, which our equilibrium model does.

2. Data and Empirical Approach

2.1. Dataset

We provide a brief discussion of the dataset here, and refer the reader to Appendix A.1 for a detailed description. Since 1988, the U.S. Department of Labor has organized *random audits* of unemployment insurance (UI) payments, investigating "the UI claimant's... efforts to find suitable work" (see Department of Labor and Administration, 2005). Known as the Benefit Accuracy Measurement (BAM) program, state UI investigators, who are regular UI case file workers, examine UI payment records and interview claimants and employers to verify all aspects of the claim that could affect benefit eligibility. Active job search – our main outcome variable – is a determination by the auditor that a UI recipient met state search requirements.

Our dataset contains records for 54,780 audited cases from the years 1988 through 2006.[3] For each unemployed individual we have data on: (i) the unemployment insurance benefit (UIB) payment; (ii) wages earned in the year prior to the spell of unemployment – the base period wages (BPW), which we measure in real terms and on a monthly basis; (iii) the highest quarter (HQ) of income earned in the year prior to the spell of unemployment; (iv) demographic characteristics (age, gender, and race); (v) information on the highest educational degree attained; (vi) the last occupation and industry the individual worked in; (vii) recall status of the previous job; and (viii) the number of weeks remaining until the UIB expire.[4] As we discuss below, we focus on the states that use the HQ system to determine UIB amounts.

Summary statistics Before discussing our empirical approach, Table 1 reports summary statistics of key variables that we later use for the empirical analysis. We report the mean and standard deviation of these variables for our entire sample (columns 1-2) and by the decile of the BPW (columns 3-22).[5] Several noteworthy patterns emerge. First, overall, a nontrivial fraction (14.6%) of unemployed individuals in our sample does *not* actively look for a job, although they are required to do so by UI state laws.[6] Second, the share of individuals engaged in active job search increases by wage deciles, ranging from 79.5% at the lowest decile to 91.2% at the highest decile. Hence, there is a substantial variation in the likelihood of search across wage deciles, which is con-

[3] While the BAM program continued to be run past this year we only have access to data up to that year.

[4] Figure A1 depicts the distribution of weeks left in our dataset showing no bunching patterns.

[5] Throughout our analysis the BPW deciles are constructed by state and year pairs.

[6] This observation is the prerequisite for the empirical analysis we carry out in this section. Had all unemployed individuals been active searchers, there would be no variation in search behavior to be explained.

sistent with the view that wages are likely to capture underlying heterogeneity in the individual returns to engage in search, an issue we discuss below.[7]

2.2. Empirical Model

Our estimating model is the following Probit specification:

$$S_{i,z,t} = 1(\alpha + \beta UIB_{i,z,t} + \gamma \vec{X}_{i,z,t} + \delta_z + \eta_t + \epsilon_{i,z,t} \geq 0), \tag{1}$$

where $S_{i,z,t}$ is a dichotomous search variable $\{0 = \text{Non-Searcher}, 1 = \text{Searcher}\}$ for individual i, in state z, in period t and $UIB_{i,z,t}$ is the level of UIB for such an individual.[8] $\vec{X}_{i,z,t}$ is a vector of covariates chosen to control, to the extent possible, for individuals' earning *potential* and includes: BPW, demographic characteristics (age, age-squared, gender, and race), education dummies, last occupation and industry the individual worked in, recall status, and weeks remaining until UIB expire. Moreover, since different U.S. states have different UI laws for calculating benefits, we include throughout state fixed effects, denoted by δ_z and hence rely on *within-state* variation. We control for time fixed effects η_t. We cluster the standard errors at the state level and deflate all monetary variables, such as UIB and BPW, by CPI measures converting them to real values. We further note that we keep all observations, including those for which UIB are capped at the state maximum.

In our empirical analysis, we remain agnostic about the mechanisms of how individuals change their search behavior in relation to changes in UIB. Rather, we focus on identifying the reduced-form coefficient that relates plausibly exogenous variation in UIB to actual job search. In Section 4 we interpret this identified parameter through the lens of our structural model.

2.2.1. Identification

UIB depend on past wages, so simply analyzing the link between UIB and the likelihood of a job search may fail to identify the effect of interest for two reasons. First, past wages may directly influence the decision to look for work: due to the positive correlation between them and benefits, one could erroneously associate the job search decision with the benefits. Second, unobserved

[7] An immediate implication of this pattern, as reported in Table 1 is that the within-decile variation in search behavior decreases by wage deciles: the higher the wage, the lower the variation in search behavior.

[8] We note that in our preferred specification we use the level of UIB as the independent variable. This is consistent with our model where the level of UIB determines the optimal search strategy. For completeness, in the Appendix, Table A2 reports the results when using the log of UIB and log of the monthly wage. None of our main findings changes.

Table 1: Mean and Std of Different Variables by Wage Deciles

Decile(s)	All		1st		2nd		3rd		4th		5th		6th		7th		8th		9th		10th	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Search	0.854	0.353	0.795	0.404	0.827	0.378	0.843	0.364	0.839	0.367	0.853	0.354	0.858	0.349	0.863	0.344	0.868	0.339	0.881	0.324	0.912	0.283
UIB	254.4	94.7	125.5	39.6	171.5	47.2	199.9	50.6	226.1	53.6	251.0	56.5	276.4	58.6	298.2	64.4	318.7	73.7	336.9	87.2	342.0	91.5
Monthly Wage	2161.0	1420.7	578.3	143.5	916.1	122.0	1183.6	144.7	1446.8	171.8	1720.0	201.3	2015.1	239.5	2343.5	282.6	2759.4	351.1	3409.9	492.2	5288.1	1482.7
Male	0.557	0.497	0.434	0.496	0.460	0.498	0.473	0.499	0.489	0.500	0.534	0.499	0.550	0.498	0.580	0.494	0.622	0.485	0.673	0.469	0.758	0.429
Age	39.822	11.778	37.550	13.138	38.235	12.761	38.782	12.578	38.785	11.807	38.962	11.510	39.479	11.506	39.657	11.286	40.240	10.897	41.966	10.404	44.644	9.777
High School	0.411	0.492	0.444	0.497	0.449	0.497	0.445	0.497	0.433	0.496	0.455	0.498	0.446	0.497	0.433	0.496	0.406	0.491	0.359	0.480	0.237	0.426
Some College	0.293	0.455	0.226	0.418	0.247	0.431	0.260	0.439	0.284	0.451	0.281	0.449	0.302	0.459	0.313	0.464	0.339	0.473	0.362	0.481	0.323	0.468
College and above	0.121	0.326	0.043	0.202	0.051	0.220	0.063	0.242	0.069	0.254	0.071	0.257	0.087	0.283	0.113	0.317	0.148	0.355	0.186	0.389	0.384	0.486
Recall	0.145	0.352	0.194	0.395	0.192	0.394	0.180	0.384	0.162	0.368	0.150	0.358	0.139	0.346	0.130	0.336	0.120	0.325	0.112	0.315	0.068	0.252
Weeks left	13.368	7.374	9.456	5.846	11.138	6.563	12.099	6.845	12.873	6.994	13.608	7.269	14.126	7.350	14.793	7.508	14.875	7.547	15.365	7.589	15.412	7.610
Black	0.159	0.366	0.243	0.429	0.204	0.403	0.191	0.393	0.179	0.384	0.158	0.365	0.161	0.367	0.151	0.358	0.129	0.335	0.110	0.312	0.066	0.248
Hispanic	0.071	0.257	0.112	0.315	0.105	0.306	0.098	0.297	0.081	0.273	0.082	0.274	0.064	0.245	0.058	0.233	0.044	0.205	0.040	0.196	0.028	0.165
Asian	0.005	0.074	0.005	0.071	0.005	0.071	0.005	0.071	0.005	0.067	0.007	0.082	0.007	0.081	0.004	0.063	0.007	0.086	0.004	0.062	0.006	0.078
Indian	0.024	0.152	0.038	0.191	0.031	0.173	0.029	0.167	0.029	0.167	0.024	0.154	0.023	0.151	0.021	0.143	0.021	0.143	0.013	0.111	0.007	0.083

Notes: UI benefits and monthly wages are expressed in real terms.

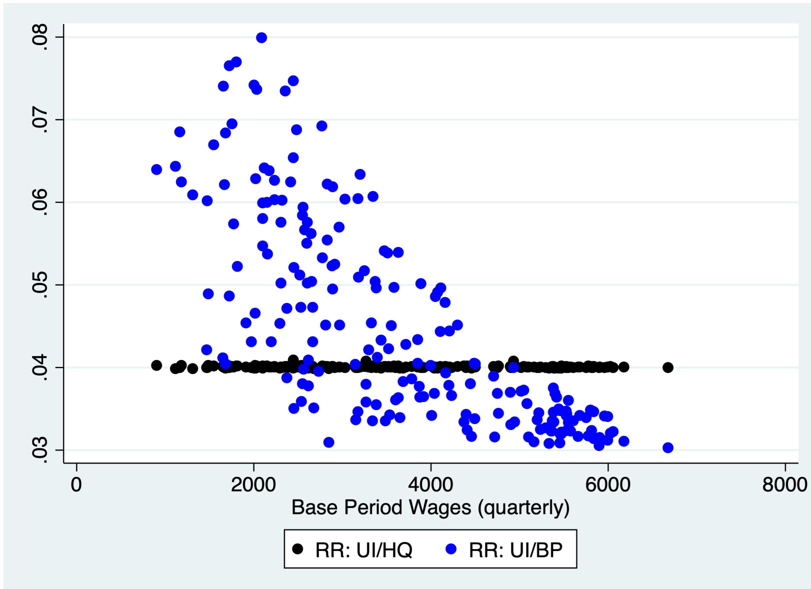
variables correlated with past wages, which also factor into the decision about whether to search, generate omitted variable bias because they affect benefits through the mechanism of past wages.

To address this challenge, we take advantage of two key aspects of our dataset. First, we have administrative information on *both* BPW and UIB. Second, in our sample of states, UIB are not only a function of BPW but also exhibit substantial variation even after controlling for BPW. Specifically, our identification makes use of the fact that, in most U.S. states, UIB that individuals receive depend on their *highest quarter* of earnings during the previous year, and thus on the *dispersion* of earnings across quarters. As Department of Labor and Administration (2005) notes, "*depending on the distribution of wages in the base period, workers with the same total base period wages can have... different weekly benefit amounts.*" Hence, the UIB amount is a *non-stochastic* function of the HQ wage, with the function itself varying across states and over time within a given state (see Appendix A.1 for the list of states with the HQ system in our sample). To the best of our knowledge, this source of variation in the generosity of UIB conditional on BPW has not been exploited before for the purpose of estimating the effect of UIB on the likelihood of search.[9]

Due to the presence of the HQ rule, UIB are not a deterministic function of BPW. Crucially, this allows us to estimate the effect of UIB on active job search controlling for BPW. For visual exposition purposes, consider the state of Arizona which uses a replacement ratio of 0.04 of HQ earnings to determine UIB. As is evident in Figure 1, which depicts for each individual both the replacement rate (UIB to BPW) and the ratio of UIB to HQ wages (which simply recovers the UIB law in Arizona), the replacement rate differs across individuals with the *same* BPW. More generally, it is of interest to explore whether UIB exhibit variation once our covariates are conditioned on. In Table A1 in Appendix A.1, we calculate for each subsample determined by BPW the unexplained variation in the HQ. We note that for the deciles for which we find below a significant effect of UIB on search (deciles 2nd-7th), there is substantial unexplained variation in HQ as measured by the relative low values of the R^2.

[9]Commonly used datasets to study the effects of UIB, such as the Current Population Survey, the Survey of Income and Program Participation, and the Panel Study of Income Dynamics do not contain individuals' qualifying income nor reliable information on the benefit amounts they actually receive. To overcome these issues, early studies based on those datasets rely on estimates of benefit eligibility and amounts, not on the actual amount of benefits collected (Blank and Card, 1991; Gruber, 1997; Chetty, 2008). Our data set, therefore, offers the following unique advantages over others. First, information on job search is not self-reported but based on the conclusion of an auditor's independent investigation. Second, BPW and UIB amounts alike come from administrative records.

Figure 1: Variation in Replacement Rates



Notes: 199 observations for the state of Arizona over the years 2002 and 2003 for which UI benefits are *below* the maximum weekly amount of $205. In this graphical example we do not include observations for which the benefits are at the state's maximum, which assure the $\frac{UI}{HQ}$ is exactly 0.04.

It is natural to wonder whether the variation in the HQ earnings, conditional on BPW, is plausibly exogenous. We address this concern as follows. First, in our empirical analysis we condition on a rich set of covariates; should any unobservable variable that affects the decision to look for work have a bearing both on the temporal distribution of wages and, hence, on UIB, only because of the variable's influence on past wages and on the other covariates that we condition on, our estimates will reveal the effect of UIB on search. Second, in an attempt to reduce concerns that omitted variables such as individual skills may be biasing our results, we allow for *unrestricted heterogeneity* in the effect of UIB on job search across earning levels by conducting our analysis for each BPW decile separately. To the extent that individuals with higher skills are also the ones with higher BPW, carrying out the analysis by subsample and further controlling for BPW in each, increases confidence that skills are being controlled for.[10] Third, placebo tests and coefficient stability analysis suggest that the temporal variability of earnings does not drive the results through channels other than that of its impact on UIB.[11]

[10] Within each BPW decile we further control for the actual continuous value of BPW.

[11] We refer the reader to Appendix B where we discuss the results of a Regression Kink Design analysis.

2.2.2. Results

Table 2 presents the regression estimates of equation (1) with the standard errors reported in parenthesis. Before discussing the effects of UIB, we briefly address the effect on active job search of the other variables. All else being equal, the likelihood of active search increases with age but at a tapering rate, as implied by the positive coefficient estimate on the age variable and the negative one on the age-squared variable. The coefficients on the education dummies (with high school dropouts serving as the excluded group) are estimated to be positive, with college graduates most likely to actively seek employment.

With respect to the effect of UIB on the likelihood of active job search, we find that for deciles 2-7 the coefficient for UIB is positive and statistically significant with *p*-value of 0.0%, 0.5%, 1.1%, 4.6%, 6.8%, and 3.5% across these deciles respectively.[12] To provide a "monetary" quantification, we note that the decile specific coefficients imply that an additional \$100 weekly UIB would increase the search likelihood on average by 4.57% percentage points.[13] Similarly, this coefficient translates to an average elasticity across deciles 2-7 of the likelihood that an individual engages in active job search with respect to UIB of 0.126.[14]

Furthermore, we report in Table 3 the predicted probability of search at the mean value of each UIB decile. The Probit regression is run on the entire sample and every other covariate is *held constant* at its mean value over the entire sample rather than within BPW decile-based subsamples. This isolates the effect of UIB across deciles due to the mean UIB value within a decile. For the deciles we found a statistically significant effect (deciles 2-7) the estimated effect ranges from 0.826 to 0.885. Hence, in real terms, an increase of \$128 in the UIB (from the second to seventh decile) increases the search likelihood by slightly less than six percentage points.

2.2.3. Placebo Tests and Stability Analysis

To examine the potential concern that the HQ wage captures unobservables that directly affect both search and UIB, over and beyond the BPW that we condition on, we proceed by considering a placebo test and a coefficient stability analysis.

[12]For the entire sample when not conditioning on the BPW decile we find the coefficient on UIB to equal 2.106, estimated with a *p*-value of 6.5%.

[13]This is the average of the percentage points increase in the search likelihood across deciles 2-7 due to an increase of \$100; 3.53%, 3.74%, 4.80%, 4.62%, 4.14%, 6.58% respectively.

[14]For deciles 2-7 the specific elasticity values are 0.070, 0.086, 0.125, 0.131, 0.127, 0.219, receptively.

Table 2: Probit Regression for Subsamples Defined by Wage Deciles

Decile	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
UIB	0.794	3.944***	4.367***	5.627**	5.885**	5.718*	8.932**	6.861	-0.686	-1.751
	(2.646)	(1.049)	(1.550)	(2.202)	(2.952)	(3.132)	(4.244)	(4.520)	(4.449)	(3.035)
Monthly Wage	-1.292	-5.823*	-7.522	-9.410**	-8.037***	-5.046	-8.151***	-4.012***	0.0131	0.202
	(2.883)	(3.385)	(5.388)	(4.764)	(3.070)	(3.786)	(1.924)	(1.277)	(0.815)	(0.201)
Male	0.0360	-0.0581	0.00473	-0.00604	-0.0507	-0.00869	-0.102*	-0.0199	-0.00718	-0.0430
	(0.0357)	(0.0497)	(0.0572)	(0.0485)	(0.0864)	(0.0302)	(0.0608)	(0.0635)	(0.0435)	(0.0947)
Age	0.0221	0.0253***	0.0120	0.0210*	0.0279*	0.0540***	0.0319**	0.0258**	0.0305	0.0146
	(0.0137)	(0.00896)	(0.00810)	(0.0108)	(0.0151)	(0.0121)	(0.0142)	(0.0110)	(0.0209)	(0.0289)
Age^2	-0.000194	-0.000283***	-0.0000861	-0.000203	-0.000252	-0.000581***	-0.000330**	-0.000263**	-0.000330	-0.000218
	(0.000155)	(0.000102)	(0.0000926)	(0.000136)	(0.000186)	(0.000138)	(0.000163)	(0.000133)	(0.000235)	(0.000315)
High School	0.128***	0.0575	0.156**	0.00703	0.150***	0.0240	0.145*	0.0431	0.111	0.126
	(0.0427)	(0.0594)	(0.0651)	(0.0612)	(0.0493)	(0.0532)	(0.0837)	(0.0954)	(0.0970)	(0.118)
Some College	0.102	0.196**	0.148***	0.157**	0.0982	0.0794	0.199***	0.145	0.246**	0.176
	(0.0683)	(0.0766)	(0.0506)	(0.0705)	(0.0704)	(0.0671)	(0.0713)	(0.109)	(0.112)	(0.150)
College and above	0.301***	0.219*	0.371***	0.491***	0.189*	0.170*	0.294**	0.311***	0.467***	0.402**
	(0.114)	(0.124)	(0.137)	(0.0646)	(0.109)	(0.0870)	(0.133)	(0.0765)	(0.120)	(0.163)
Recall	0.145	0.169	0.189	0.0701	0.198	0.276**	0.130	0.182	0.0979	0.0516
	(0.101)	(0.161)	(0.151)	(0.202)	(0.196)	(0.117)	(0.201)	(0.248)	(0.236)	(0.213)
Weeks left	0.00160	0.00690	0.00558	0.00406	0.00465	0.00807***	0.00840***	0.00584	0.0119***	0.0111**
	(0.00520)	(0.00420)	(0.00412)	(0.00316)	(0.00487)	(0.00305)	(0.00197)	(0.00418)	(0.00458)	(0.00527)
Black	-0.298***	-0.311***	-0.256***	-0.293***	-0.234**	-0.301***	-0.287**	-0.186*	-0.316***	-0.360***
	(0.0868)	(0.0928)	(0.0890)	(0.0549)	(0.0955)	(0.0754)	(0.119)	(0.0985)	(0.0287)	(0.124)
Hispanic	-0.160*	-0.187*	-0.0907	-0.0861	-0.270***	-0.139	-0.110***	0.0305	-0.266**	-0.154*
	(0.0918)	(0.0997)	(0.117)	(0.0731)	(0.0589)	(0.110)	(0.0223)	(0.0927)	(0.121)	(0.0887)
Asian	-0.0454	-0.403	0.0744	-0.215	-0.243	-0.142	0.0150	-0.617***	-0.439	0.389
	(0.345)	(0.316)	(0.250)	(0.280)	(0.252)	(0.236)	(0.438)	(0.171)	(0.333)	(0.437)
Indian	-0.178	0.000302	-0.0456	-0.0107	-0.213	-0.0579	0.0721	0.0803	0.231	-0.0235
	(0.235)	(0.0650)	(0.137)	(0.0769)	(0.148)	(0.115)	(0.244)	(0.196)	(0.238)	(0.270)
Observations	5541	5466	5484	5455	5455	5491	5483	5457	5481	5406
R^2	0.128	0.102	0.111	0.109	0.115	0.113	0.111	0.108	0.118	0.141
Log lik.	-2451.9	-2260.4	-2121.1	-2144.2	-2014.7	-1986.8	-1949.5	-1901.8	-1763.8	-1385.3

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Predicted Search Probabilities

Decile	2nd	3rd	4th	5th	6th	7th
Mean UIB	171.5	199.9	226.1	251.0	276.4	298.2
Predicted Search Probability	0.826	0.841	0.854	0.865	0.876	0.885

Notes: The table reports the predicted search probabilities for deciles 2 through 7 as implied by the Probit estimated coefficient. These predicted search probabilities are calculated with all covariates, but the UIB, being held at their unconditional sample means, while the UIB is set at its decile-specific mean.

Placebo tests We estimate the same Probit regression as described above *solely* for the subsample of individuals whose UIB equal the maximum allowed by the law in the state/year of their audit. We then include the HQ wage in Equation (1), keeping all the other covariates, except for the UIB. Hence, this subsample consists of individuals who have the *same* UIB (since they are up against their state's UIB maximum) but who differ in their HQ earnings.

The logic of this approach is as follows. If the HQ wage solely affects the likelihood of search via its effect on UIB, then once UIB is fixed the HQ coefficient should be statistically insignificant, consistent with our identification assumptions above. Such a result would be supporting the view that HQ variation does not capture any unobservable variable that affects job search through channels other than UIB. Table 4 reports the estimates for the coefficient of the HQ variable for the subsample for which we found a positive effect on active search (deciles 2-7 in Table 4). As the table suggest, we fail to reject that HQ has zero impact on search for five out of the six relevant deciles. Overall, we view these placebo results as supporting our empirical strategy as they suggest that variation in HQ are likely to affect the probability of search only through its effect on UIB.

Table 4: Results from Placebo Test

Decile	2nd	3rd	4th	5th	6th	7th
HQ Wage	0.563	-0.688	0.988**	0.147	0.343	-0.011
	(1.831)	(0.587)	(.408)	(0.253)	(0.323)	(0.208)
Observations	111	402	657	1039	1636	2391

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Stability analysis To assess the robustness of our main finding of a positive effect of UIB on search, we run several Probit regressions where we include an increasingly large set of covariates (eventually arriving to our preferred specification). The results are in Table 5, where we report the estimated coefficient on UIB across deciles (the columns of the table) and specifications (the rows of the table). In the first row of the table we provide baseline Probit regression results where we condition only on state and time fixed effects. We then add BPW to the covariates in the Probit regression. We view BPW as crucial to capture the effect of possible unobserved individual skills on both search and UIB. Comparing row one and row two in Table 5, we see that including BPW indeed can have a non-negligible impact on either the UIB coefficient estimate or its significance for several deciles. In each of rows (3)-(6), we add an additional demographic variable (respectively: age and age squared; gender; education dummies; and race dummies) and note that the UIB coefficient estimate (within decile) remains fairly stable throughout the incremental inclusion of these covariates. Rows (7), (8), and (9) are particularly interesting in that they address specific threats to validity of our analysis. In row (7) we include dummy variables for the occupation and industry that an individual is in. Doing so addresses the concern that individuals in specific industries and occupations may face higher variability in their HQ (e.g., seasonal workers), and also differ in their unobservable characteristics from individuals in other occupations or industries in a way that might be driving our main result. However, the coefficient estimates reported in row (7) remain positive and statistically significant (for deciles 2-7), although their magnitude is slightly reduced. In row (8) we include the number of weeks of unemployment benefits left. Doing so could accounts for potentially different channels. For example, individuals with less weeks of benefits left may have a higher incentive to search, as they will run out of wage replacement sooner. In contrast they might get discouraged and stop searching altogether. Moreover, such individuals also face a lower probability of being audited, because audits are random and occur each week, so by having less weeks left they are subject to a lower auditing probability, and hence may have a lower incentive to search. Regardless of which of these effects prevail, the UIB coefficient estimates in row (8) are quite similar to the ones in rows (2)-(7). Finally, in row (9) we include recall status. Doing so addresses the concern that people who may be recalled to their former jobs may systematically differ from those who do not both in their unobservables, and in the variability of their HQ. However, the coefficient estimates in row (9) are again similar (within deciles) to those in rows (2)-(8).

Table 5: Stability Analysis

Decile	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
(1) State & time fixed effects	1.584	3.209**	4.094***	5.032**	5.104	5.554	6.292	4.630	0.111	-1.347
	(1.925)	(1.435)	(1.166)	(2.425)	(4.212)	(3.814)	(5.207)	(4.811)	(4.346)	(2.865)
(2) + Monthly wage	1.933	3.946**	5.037***	6.506**	6.979*	6.890*	9.434*	7.019	-0.326	-1.716
	(2.280)	(1.564)	(1.500)	(2.660)	(4.218)	(3.627)	(5.060)	(5.098)	(4.753)	(2.956)
(3) + Age	2.163	3.742**	5.145***	6.398**	6.998	6.438*	9.225*	6.975	-0.472	-1.704
	(2.299)	(1.547)	(1.530)	(2.636)	(4.300)	(3.795)	(5.087)	(5.173)	(4.797)	(3.005)
(4) + Gender	2.057	4.115***	5.013***	6.599***	7.353*	6.641*	9.531*	7.023	-0.496	-1.781
	(2.245)	(1.265)	(1.237)	(2.425)	(4.049)	(3.659)	(4.978)	(5.100)	(4.777)	(3.002)
(5) + Education	1.829	3.763***	4.643***	5.888**	7.219*	6.576*	9.600*	6.944	-0.536	-1.860
	(2.276)	(1.227)	(1.346)	(2.581)	(4.119)	(3.684)	(5.069)	(5.074)	(4.746)	(2.982)
(6) + Race	1.620	3.816***	4.386***	5.734**	6.966*	6.250*	9.397*	6.885	-0.548	-1.827
	(2.377)	(1.205)	(1.468)	(2.555)	(4.030)	(3.681)	(5.020)	(5.063)	(4.657)	(3.038)
(7) + Occupation & industry	0.757	3.246***	4.073***	5.383**	6.047*	5.853*	8.804*	6.787	-1.040	-1.715
	(2.358)	(1.124)	(1.343)	(2.264)	(3.286)	(3.203)	(4.541)	(4.658)	(4.241)	(2.854)
(8) + Weeks left	0.985	4.235***	4.793***	5.794**	6.489*	6.475*	9.212**	6.968	-0.881	-1.803
	(2.652)	(1.361)	(1.353)	(2.401)	(3.614)	(3.333)	(4.527)	(4.694)	(4.534)	(3.174)
(9) + Recall	0.794	3.944***	4.367***	5.627**	5.885**	5.718*	8.932**	6.861	-0.686	-1.751
	(2.646)	(1.049)	(1.550)	(2.202)	(2.952)	(3.132)	(4.244)	(4.520)	(4.449)	(3.035)

Notes: The table reports the coefficients on UIB for each BPW decile. The first row reports the estimates of the effect of UIB when we do not control for any other variable besides a state fixed effect and a time fixed effects. As we move down, we add each time an additional variable. Specifically, in row (2) we add the monthly wage, in row (3) we add the age and age^2, in row (4) we add the gender, in row (5) we add the education variables, in column (6) we add the race variables, in row (7) we add the occupation and industry variables, in row (8) we add the weeks left variable, and in row (9) we add the recall status. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.2.4. Discussion

The empirical results presented in this section cannot identify the specific economic mechanism determining the positive effect of UIB on search. Yet, they are consistent, as we show below in our theoretical model, with the idea that risk-averse individuals face monetary fixed costs of job search. Higher benefits help pay for such fixed costs, which facilitates active search.

The findings presented in Table 3 further support the notion that a positive effect of benefits on job search might stem from liquidity constraints: by the time these unemployed individuals are out of work, their previous earnings are gone and irrelevant, so that most of their economic decisions, including whether to search for a job, rely on the extent of contemporaneous earnings, i.e., unemployment benefits.

Moreover, we note that while there is limited direct evidence on the exact monetary magnitudes of search costs, the U.S. tax code specifically allows for various items related to job search to be deducted, suggesting that policy makers have recognized the presence of these costs. Overall, these results are consistent with the literature highlighting the role of liquidity constraints for the unemployed (e.g., Chetty, 2008) as well as the important literature that highlights the importance of such liquidity constraints for hand-to-mouth individuals and shows that such hand-to-mouth individuals are a sizable fraction of consumers in the economy (e.g., Jappelli, 1990; Jappelli and Pistaferri, 2010; Kaplan and Violante, 2014; Kaplan, Violante and Weidner, 2014; Jappelli and Pistaferri, 2014).[15]

3. A Partial-Equilibrium Model of Costly Job Search

What are the mechanisms that rationalize our empirical findings? To address this question, we develop a simple yet general non-parametric model that encompasses a few possible channels through which UI affects the likelihood of search. Our objective is to determine under which conditions and for which type of costs (monetary or other utility non-monetary costs) increase in

[15] We note that an alternative, complementary hypothesis is one in which unemployed individuals recognize the possibility of being audited. In that case, if the audit is random, then the higher the benefits, the higher the cost of being detected not exerting search effort, and thus the higher the incentives to engage in search. While we do not have direct evidence on this mechanism, we note that the coefficient stability analysis presented in Table 5 provides suggestive evidence against it. Notably, the estimate of the coefficient on UI benefits remains virtually unchanged when we include along the covariates the number of weeks lefts until benefit expiration. Weeks left until benefit expiration can be thought of as a proxy for detection probabilities: the higher the number of weeks left, the higher the unconditional probability an unemployed individual to be audited. While not definitive, our stability analysis casts doubts on the relevance of the detection probability hypothesis.

benefits yields a higher likelihood of search. Based on the insights from this model, we develop a general-equilibrium model in the next section.

The model's main features are: (i) risk-averse individuals; (ii) the presence of search frictions that prevent the instantaneous matching of job seekers with available jobs; and (iii) two potential types of costly job search. The first cost is a "monetary cost," i.e., after individuals engage in a job search their consumption declines.[16] Job search is painful for risk-averse individuals because they incur a cost when consumption is already low due to job loss. The second cost is the "utility cost" of search, which lowers instantaneous utility but does not entail a consumption loss. It is important to note that consistent with our Probit analysis, the model renders predictions on the relation between benefits and a dichotomous variable indicating whether an individual is a searcher or not, akin to a standard binary response model.

Environment and search decision We analyze the problem of an individual facing the decision of whether to look for work. This involves specifying preferences and budget constraints, with the production side of the economy and wage determination left unspecified. In this sense, we focus on a decision theory problem in a partial-equilibrium setting, abstracting from the equilibrium feedback effects of UIB on wages and job-finding probabilities.

In the model, an individual can be in three labor-market states: (i) employed at a wage, w, and consuming $c = w$; (ii) unemployed, searching and paying the fixed cost $s \geq 0$, collecting benefits, b, and consuming $c = b - s$; (iii) unemployed, not searching, collecting benefits, and consuming $c = b$.[17] Note that by reducing consumption, s captures a *monetary cost* of searching.[18]

The individual's choice between searching and not-searching is described by

$$V(b) = \max \{V_u(b), V_n(b)\}, \tag{2}$$

[16] Mazur (2016) adopts a similar assumption in the context of a McCall search model. He shows that monetary search costs yield the well-documented spike in search effort at the time of benefit exhaustion.

[17] In fact, individuals can be in two other labor-market states that we do not model: either searching or not-searching without collecting benefits (because, though eligible, they do not apply for them). While empirically relevant, these individuals, unfortunately, are not part of our dataset. More substantively, modeling the UI application margin could be important for quantifying the effects of changes in benefit generosity. For instance, more generous benefits could in principle lead more people to apply for them. Given this mechanism, the question then becomes what those individuals do conditional on applying for and collecting benefits. The model we set up here is tailored to answer this latter question.

[18] Given the partial-equilibrium nature of this setting, we can normalize the wage to one, so that b can be interpreted as benefits or as a replacement rate.

where $V_u(b)$ and $V_n(b)$ are the values of searching and not-searching respectively, given by

$$V_u(b) = u(b-s) - \Phi(s) + \beta \left[p_S(b) V_e(b') + (1 - p_S(b)) V(b') \right], \tag{3}$$

$$V_n(b) = u(b) + \beta \left[p_N(b) V_e(b') + (1 - p_N(b)) V(b') \right]. \tag{4}$$

The utility function $u(\cdot)$ is strictly increasing, concave, and twice continuously differentiable. $\Phi(s)$ captures the utility loss from "other" *non-monetary* search costs with $\Phi'(s) \geq 0$ and $\Phi(0) = 0$. $p_S(b)$ denotes the probability of finding a job conditional on searching and $V_e(b)$ is the value of working, which we leave unspecified here.[19] Also, henceforth, we assume that $V_e(b) > V(b)$, for all b, so that individuals always prefer working to either searching or not-searching.

The individual's decision is to search if and only if $V_u(b) > V_n(b)$. The optimal search decision follows a reservation rule: for a given UIB level b, there is a unique cutoff on the fixed search cost, s^*, such that if $s \geq s^*$ the individual does not search, and if $s < s^*$ the individual searches. Formally, the cutoff value s^* is implicitly determined by the indifference condition

$$\beta \left(p_S(b) - p_N(b) \right) \left[V_e(b') - V(b') \right] = u(b) - u(b - s^*) + \Phi(s^*), \tag{5}$$

such that the net benefit from searching, on the left-hand side, equals the net utility cost from searching on the right-hand side.[20] All else being equal, the higher the net benefit from working, $V_e(b') - V(b')$, the greater the value of the search cost s^* that makes an individual indifferent between searching and not-searching. By contrast, an individual with a higher disutility of search has a lower search cutoff and so is less likely to search.

Role of monetary search costs Let $G(b, b')$ indicate the left-hand side of (5), such that we can rewrite the indifference condition in more compact form as

$$G(b, b') = u(b) - u(b - s^*) + \Phi(s^*). \tag{6}$$

[19] Our notation makes explicit that $p_S(b)$ and $V_e(b)$ may depend on b. This is the case in the standard search-and-matching model, where higher b leads to higher wages that in turn depress firms' vacancy postings and the probability of finding a job. In this model, the dependence of $V_e(b)$ on b derives from the feature that wages are determined via Nash bargaining, in which case the higher b, the greater the opportunity cost of accepting a job, the higher the wage.

[20] The left-hand side of (5) is independent of the search cost s, while the right-hand side is monotonically increasing in s. Standard arguments imply that if a solution to equation (5) exists, it is unique.

We assume that the UIB next period can be modelled as $b' = \lambda\bar{b} + (1-\lambda)b$, where $\bar{b}$ is a long-run level of b and $\lambda \in [0,1]$ is a parameter governing the persistence of changes in current UIB. Specifically, (i) if $\lambda = 0$, $b' = b$, such that any change in b represents a *permanent* change in UIB; (ii) if $\lambda = 1$, $b' = \bar{b}$, such that a change in b is *temporary*, lasting for only one period; (iii) if $0 < \lambda < 1$, a change in b is *persistent*, lasting a few periods.

Total differentiation of equation (6) yields

$$\frac{\partial s^*}{\partial b} = \frac{G'(b,b') + u'(b-s^*) - u'(b)}{u'(b-s^*) + \Phi'(s^*)} \lesseqgtr 0, \tag{7}$$

where

$$\begin{aligned} G'(b,b') \equiv \partial G(b,b')/\partial b = {} & \beta\left(p_S'(b) - p_N'(b)\right)\left[V_e(b') - V(b')\right] \\ & + \beta\left(p_S(b) - p_N(b)\right)(1-\lambda)\left[V_e'(b') - V'(b')\right] \lesseqgtr 0. \end{aligned} \tag{8}$$

The sign of the comparative statics depends on the relative strength of two forces: the change in the net benefit from searching, $G'(b,b')$, versus the change in the net utility cost from searching, $u'(b-s^*) - u'(b)$.[21]

Consider first the case in which $G'(b,b') = 0$. Unambiguously, $\partial s^*/\partial b \geq 0$. That is, higher UIB raise the search cutoff s^*, implying a higher likelihood of job search.[22] A necessary condition for this result is the presence of a *monetary search cost*. We refer to this effect as the consumption or "liquidity channel" of UIB. Absent a monetary cost of search, and in the presence of a time cost of search only, expression (7) implies that $\partial s^*/\partial b = 0$. In this case, there is no effect of b on the search cutoff s^*, so no effect on the search likelihood. Thus, there must be a "consumption/liquidity" cost of search for the model to square with the empirical finding that the search likelihood increases with UIB generosity.

The second case is one where $G'(b,b') < 0$. Here the theory predicts an ambiguous effect of b on s^* as what matters is the relative strength of two competing forces. On the one hand, higher UIB reduce the net benefit from searching. On the other hand, the same UIB increase reduces the utility cost of job search. Which of the two effects dominates depends on a number of factors, including parameter values describing preferences and technology, as well as the market structure, e.g., the

[21]We do not consider the case $G(b,b') > 0$ as it holds under arguably implausible conditions. Specifically, in this scenario one can show that, everything else equal, the value of working becomes, vis-à-vis the value of not-working, more attractive the higher UIB are.

[22]This result comes from the concavity of the utility function: $u'(x) \geq u'(y)$ if $x \leq y$.

extent of frictions and wage bargaining protocol.

Yet, for our purposes, in this case, if, as in our empirical results, higher UIB raise the job search likelihood, $\partial s^*/\partial b > 0$, then, again, as in first case above, the cost must be monetary. To see this simply note that, absent a monetary cost, the sign of $\partial s^*/\partial b$ would be negative since $G'(b, b') < 0$ and the term $u'(b - s^*) - u'(b)$ would equal zero. So in this case as well, a necessary condition to reconcile the theory with our empirical findings is the presence of a monetary cost.

4. A General-Equilibrium Model

Based on the insights from the partial-equilibrium model in the previous section, we proceed by presenting a parametric quantitative general-equilibrium (GE) model that we later use as a laboratory to examine the impact of different UI policy reforms. The model's main features are: (i) search frictions that give rise to unemployment as in the Diamond-Mortensen-Pissarides (DMP) search-and-matching model; (ii) a notion of free-entry equilibrium in which the ratio of posted vacancies to the mass of searchers determines the tightness of the market and thus the probability of finding a job conditional on searching; (iii) a search decision in which risk-averse individuals face a "monetary cost" for job searches and choose whether to look for work.[23]

The key advantage of the GE structure is that it enables us to gauge the equilibrium feedback effects of UIB reforms on the search likelihood, market tightness, and job-finding probabilities. These implications cannot be addressed in the context of the non-parametric model presented above, let alone our empirical estimates. Importantly, we make the government budget constraint (that it holds for each reform) a key feature of the GE nature of the model. For example, a rise in UIB that requires additional tax revenues may be financed by an increase in labor tax rates, which is likely, in itself, to have important equilibrium effects on search decisions, wages, and so on.

The key tradeoff we are interested in analyzing is as follows. In the model, as in our empirical results, increased UIB would, ceteris paribus, push individuals to search for work. However, consistent with a vast literature, higher benefits could lead to a higher equilibrium wage, which in turn depresses vacancy posting.[24] The overall effect on the employment rate is, in principle, ambiguous given the interaction of these two opposing forces: on the one hand, the liquidity effect

[23] We emphasize the importance of considering risk-averse agents because, without this assumption (i.e., under linear utility), there is no conceptual difference between the monetary cost of search and other dis-utilities associated with costly search; i.e., subtracting a consumption cost from a linear utility or a time cost would be equivalent. Thus, consistent with our interpretation of the search cost being monetary, we proceed with the assumption that the utility function exhibits risk aversion.

[24] The strength of these equilibrium effects critically depends on the details of the wage setting mechanism.

on search tends to expand the pool of individuals looking for work; on the other, the disincentive effect on labor demand reduces the speed at which job searchers find jobs. We use the model to quantify these mechanisms and evaluate their relevance for UI policy.

4.1. Environment

Before presenting the setup of the model in more detail, it is worth emphasizing that the model represents a minimal perturbation of the prototype search-and-matching DMP model. This greatly simplifies comparison with existing work and allows for a simple analysis of the impact of costly job search. However, this simplicity comes at the cost of descriptive realism, as many aspects that are absent from the benchmark DMP model (such as accumulation of assets) are left out of the analysis.

Preferences Time is discrete and continues forever, indexed by $t = 0,1,\ldots,\infty$. The economy is inhabited by a unit mass of infinitely-lived, risk-averse individuals whose preferences over consumption $c \geq 0$ are described by the CRRA utility function $u(c) = c^{1-\gamma} / (1-\gamma)$, where γ is the coefficient of relative risk aversion. They discount future values with the discount factor $\beta \in (0,1)$, and maximize their lifetime utility,

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t). \tag{9}$$

Budget constraints First, if the individual works at the wage w_t, then her consumption is given by $c_t = (1-\tau)w_t$, where $\tau \in [0,1]$ denotes a tax rate on labor income. Second, consumption is given by $c_t = bw_t - s$ if the individual is unemployed, collecting benefits bw_t, given a replacement rate b, and engaging in actual job search, in which case she pays the search cost s. Finally, if the individual is unemployed, collecting benefits, but not searching, then her consumption is given by $c_t = bw_t$. These last two categories, (i) unemployed collecting benefits and engaged in search, and (ii) unemployed collecting benefits and not-searching, represent the universe in our empirical analysis.

Search costs Individuals differ in terms of their cost of searching. Specifically, the monetary cost of search $s \geq 0$ is independent and identically distributed (i.i.d.) across individuals. For simplicity's sake we assume that, once the individual gets her initial draw, the value of s stays the same forever. As discussed above, such cross-sectional variation in s captures several potential sources of unobserved heterogeneity that we leave unspecified here, including, but not limited to, child care costs, commuting and clothing expenses, employment agency fees, and so on.

Replacement rates We assume that individuals differ in terms of their replacement rates, $b \in [b_{\min}, b_{\max}]$, defined as the ratio of UIB to wages. There are three reasons for heterogeneity in replacement rates.

First, such heterogeneity in b captures the large dispersion in replacement rates we documented from our administrative data *even* conditional on last period wages. Indeed, it is this variation in the data we leverage to identify the marginal effect and so the elasticity of the likelihood of active search with respect to UIB.

Second, as we show below, the model implies that the magnitude and the sign of the effect of changes in UIB on active search vary across the distribution of replacement rates. Hence, based on theoretical grounds, the underlying heterogeneity in replacement rates likely has important implications for the aggregate as well as the distributional consequences of UIB policy reforms.

Third, modelling heterogeneity in replacement rates, and thereby UIB, allows us to discipline the model by reproducing the predicted search probabilities estimated from our data, as reported in Table 3, without relying on policy counterfactuals. That is, as we discuss below in the calibration section, we use the mapping between UIB and search probabilities as a way to calibrate some of the key parameters in the model.

Market structure As is common in the DMP literature we assume that production requires a match between one worker and one firm. After a match ("job") is created, output is produced with a linear production function in which labor is the only input.

We assume for simplicity's sake that labor markets are segmented by replacement rates b. Firms post vacancies in the submarket with the highest expected payoff, knowing with certainty the value of the replacement rate b that the unemployed carry in that submarket.[25] The mass of firms in each submarket is determined in free-entry equilibrium, independent of other submarkets.[26]

[25]Consistent with the repeated cross-sectional nature of our dataset, we assume that an individual UIB is fixed. In unreported results we extended the model to have a stochastic b, which significantly complicates the analysis without altering in any significant way the results.

[26]Market segmentation provides analytical tractability. To grasp this, consider another market structure in which markets are not segmented so that individuals with different replacement rates all search in the same market. In such an environment, with Nash bargaining, vacancy-posting firms would need to keep track of the distribution of unemployed workers across replacement rates. In a free-entry equilibrium, job-finding probabilities would become a function of the distribution of replacement rates, an infinitely dimensional object that cannot be characterized analytically.

In each submarket b, matching is subject to a search friction. The ratio of vacancies to searchers $\theta(b)$ denotes tightness of submarket b. We emphasize that $\theta(b)$ is an equilibrium object, and that as such it is taken parametrically by the individuals. Also, we denote the probability that an individual meets a vacancy by $p(\theta(b))$, where $p : \mathbb{R}_+ \rightarrow [0,1]$ is a strictly increasing function with $p(0) = 0$. And the rate at which a vacancy meets a searcher by $q(\theta(b)) = p(\theta(b))/\theta(b)$.[27]

Government A government runs a balanced budget on a period-by-period basis. To this end, the labor tax rate τ, which individuals take as given, is the endogenous instrument we adjust to guarantee that total labor taxes equal total benefits across all markets at all times.

4.2. Individual's Problem

In each submarket b, individuals can be in three different labor-market states: (i) employed (e), (ii) unemployed and searching (u), and (iii) unemployed and not-searching (n).

Denote the value of being employed in submarket b by $V_e(b)$. Similarly, the value of being unemployed and searching is denoted by $V_u(b)$, while the value of being unemployed and not-searching in submarket b is denoted by $V_n(b)$. Formally,

$$V_e(b) = u(c_e) + \beta \left[\delta \max \left\{ V_u(b), V_n(b) \right\} + (1-\delta) V_e(b) \right], \tag{10}$$

where $c_e = (1-\tau)w(b)$ is consumption if employed and $w(b)$ is the wage whose determination we describe below. The parameter $\delta \in [0,1]$ is an exogenous and constant job destruction rate, which is the same in all submarkets. Upon separation (occurring with probability δ), the unemployed individual chooses between searching and not-searching. The two value functions associated with being unemployed are given by

$$V_u(b) = u(c_u) + \beta \left\{ p(\theta(b)) V_e(b) + [1 - p(\theta(b))] \max \left\{ V_u(b), V_n(b) \right\} \right\}, \tag{11}$$

$$V_n(b) = u(c_n) + \beta V_n(b), \tag{12}$$

where $c_u = bw(b) - s$ and $c_n = bw(b)$ if searching and not-searching, respectively. Given that we limit our analysis to comparisons across steady states (excluding transitional dynamics across

[27] We note that the way we specified the market structure is such that the search cost is *not* contractible and thus is not part of the bargaining problem. This is done for simplicity of the presentation as the key advantage of this assumption is that the resulting wage does not depend on s, so that individuals with the same replacement rate b, but different values of the search cost, s, have the same wage. In Appendix E we present an extension of the model laid out here where the search cost is formally part of the bargaining problem.

policy regimes), if an unemployed individual engages in search she will continue doing so. Since finding a job is only possible when searching, for an employed individual $\max\{V_u(b), V_n(b)\} = V_u(b)$, implying that we can rewrite equation (10) as

$$V_e(b) = u(c_e) + \beta\left[\delta V_u(b) + (1-\delta)V_e(b)\right]. \tag{13}$$

4.3. Firm's Problem

Vacancies can either be filled, which creates a job, or unfilled. The value of a job in submarket b is

$$J(b) = \epsilon - w(b) + \beta\left[\delta V + (1-\delta)J(b)\right], \tag{14}$$

where ϵ is the output of a match that is the same in all submarkets and V is the value of posting a vacancy. In an equilibrium with free entry, the value of an unfilled vacancy is zero at all times and in all submarkets, so the expected cost of posting a vacancy equals the discounted value of a job,

$$\frac{k}{q(\theta(b))} = \beta J(b), \tag{15}$$

where $k \geq 0$ is the unit cost of posting and maintaining a vacancy.

4.4. Wage Setting

We consider three alternative wage setting mechanisms which differ in terms of wage flexibility: (i) the Nash-bargaining protocol, arguably the benchmark of "flexible wages" in the literature; (ii) "sticky wages," which involves fixing the wage in each submarket at a specific value in the bargaining set, and thus equilibrium forces are absent since wages and the probability of finding a job conditional on searching are invariant to changes in the UIB, and (iii) "semi-flexible wages" which are a hybrid of these two bounds for the degree of wage rigidity and the effects of changes in UIB policy.

Nash-bargaining wages When a searcher and a firm meet, they enter bilateral Nash-bargaining. We assume, as is standard, that bargaining resumes every period and that the wage is determined according to

$$w^{\text{Nash}}(b) = \arg\max\left[V_e(b) - \tilde{V}_u(b)\right]^{\rho} J(b)^{1-\rho}, \tag{16}$$

where ρ captures the individuals' bargaining weight and $\tilde{V}_u(b)$ represents the outside option of the unemployed individual when excluding the search cost, i.e.

$$\tilde{V}_u(b) = u(\tilde{c}_u) + \beta \left\{ p(\theta(b)) V_e(b) + [1 - p(\theta(b))] \tilde{V}_u(b) \right\}, \tag{17}$$

where $\tilde{c}_u = bw(b)$. The solution to the Nash-bargaining problem yields a modified sharing rule that accounts for the curvature of the utility function and the flat-rate tax on labor income,

$$(1-\tau)\rho u_c(c_e) J(b) = (1-\rho)\left[V_e(b) - \tilde{V}_u(b)\right]. \tag{18}$$

Under Nash bargaining, the disincentive effect of UIB on the job-finding probability arises from the bargaining problem: the higher the replacement rate, the higher the bargained wage, and the lower the job-finding rate conditional on searching.

Sticky wages In a model with search frictions like ours, the wage is indeterminate.[28] Based on this insight, Hall (2005) introduces wage stickiness into an otherwise standard search-and-matching model of unemployment.[29]

Semi-flexible wages The empirical literature has not converged on a specific magnitude of the effects of UIB reform on job-finding rates. By considering these two wage-setting mechanisms, we let the model encompass different "bounds" on how UIB reform affects wages and, in turn, job-finding rates.[30] Naturally, the model can be calibrated to target a specific elasticity of a UIB reform on job-finding rates with usual modelling approaches in the literature (e.g., Yedid-Levi, 2016).[31]

[28] In each submarket, there is a bargaining set with a continuum of wages compatible with equilibrium: $\mathcal{W}(b) = [\underline{w}(b), \overline{w}(b)]$, where the lower bound of the set is defined as $\underline{w}(b) = V_e(b) - V_u(b)$ and the upper bound as $\overline{w}(b) = J(b)$. Nash-bargaining selects one wage in that set. Where exactly the Nash-bargaining wage locates in that set depends on the value of the worker's bargaining weight ρ.

[29] When changes in the environment shift the boundaries of the bargaining set, the wage remains constant, provided it stays inside the bargaining set. Such wage rigidity satisfies the criterion that no bilateral gains from trade are foregone, so that it is immune to Barro's critique of sticky-wage models (Barro, 1977). The decentralization of the equilibrium with sticky wages takes two steps. First, we solve for the equilibrium of the model with Nash bargaining. Second, we use $w^{\text{Nash}}(b)$ implied by (16) as the *fixed* wage of the sticky-wage economy per each b even after UIB policy changes.

[30] We note that one possible interpretation of these bounds is that the sticky wage version of the model, in which job-finding rates do not react to benefit changes, is a better approximation of the short-run response, while the "flexible Nash-bargaining" solution better approximates the long-run response to the policy reform.

[31] In this modification we introduce an additional parameter that links the bargaining power of the worker to labor market tightness, in a way that tames the response of wages to changes in UIB. Formally, the bargaining power ρ is now expressed as $\rho(\theta) = \rho_0 / \left[\rho_0 + (1-\rho_0)(\theta_0/\theta)^{\zeta}\right]$, where ρ_0 and θ_0 refer to the bargaining weight and tightness ratio in the benchmark model, respectively. Note that when $\zeta = 0$ the model nests the benchmark Nash bargaining case with constant bargaining weight.

For exposition purposes we pick the model to match the elasticity in Chetty (2008) for which the results lie between the two other wage settings.

4.5. Equilibrium

As in the standard DMP model, the equilibrium of our model economy remains block-recursive. That is, we can solve for the wages and tightness ratios independently of the stocks of employment, unemployment, and the mass of searchers. Equipped with wages and tightness ratios, we can then calculate search cutoffs $s^*(b)$ and thus the mass of searchers $G(s^*(b))$ in each submarket.

Market tightness and wages In each submarket, the free-entry condition (15) determines the market tightness ratio given the wage,

$$\frac{k}{q(\theta(b))} = \frac{\beta\left[\epsilon - w(b)\right]}{1-\beta\left(1-\delta\right)}. \tag{19}$$

Then, the modified sharing rule (18) determines the wage given the tightness ratio,

$$(1-\tau)\rho u_c(c_e)\frac{k}{\beta q\left(\theta(b)\right)} = \frac{(1-\rho)\left[u\left(c_e\right) - u\left(\tilde{c}_u\right)\right]}{1-\beta\left[1-\delta-p(\theta(b))\right]}, \tag{20}$$

where $c_e = (1-\tau)w(b)$, $\tilde{c}_u = bw(b)$, and τ is the tax rate that balances the government budget.

Search cutoff In each submarket b, the search decision satisfies a reservation policy rule such that if $V_u > V_n$ the individual searches; otherwise, if $V_u \leq V_n$, she does not search. The indifference condition $V_u = V_n$ implies a cutoff value s^*, such that if $s < s^*$ the individual searches, whereas if $s \geq s^*$ the individual does not search.

Formally, in a steady state (with respect to tax and UIB policy), the search cutoff can be shown to be implicitly determined by

$$\frac{(1-\beta(1-\delta))u(c_u) + \beta p(\theta(b))u(c_e)}{1-\beta(1-\delta)+\beta p(\theta(b))} = u(c_n). \tag{21}$$

The right-hand side of equation (21) is invariant to the search cost. For a given tightness ratio $\theta(b)$, the left-hand side is instead monotonically decreasing in s through the term $u(c_u)$, where $c_u = bw(b) - s$. Thus, if an intersection exists, standard argument implies that the cutoff value is unique. In addition, the mapping $s^*(b)$ between the search cutoff and the replacement rate b is invertible: the higher b is, the higher the cutoff s^* that makes the individual indifferent between searching and not-searching is. Since the measure of searchers is the cumulative density function at s^*, it follows that, everything else equal, the measure of searchers increases with b.

5. Bringing the General-Equilibrium Model to the Data

In this section we specify functional forms and parameter values. The baseline parameterization consists of two steps. First, to ease comparison with previous work, we calibrate a subset of parameters based on common values in the literature. Second, we estimate the remaining parameters to match a select number of empirical targets.

5.1. Parametrization

Preferences There are two parameters describing preferences: β and γ. We calibrate our monthly model to accord with a 4% annual interest rate, implying that the time discount factor β is set equal to 0.997. The coefficient of risk aversion γ is set equal to 2, which implies an elasticity of intertemporal substitution of 0.5, a value which is commonly used in the literature.

Replacement rates Let $\vec{b}$ denote the vector of replacement rates across the different submarkets. To calibrate this vector we create an evenly spaced grid, ranging from the lowest value $b_{\min} = 0.4$ to the highest value $b_{\max} = 0.6$. These lower and upper bounds correspond to the values of the inter-quartile range of the replacement rates distribution we recover from our data.

Labor market In each submarket, a matching technology yields the number of matches m as a function of the mass of searchers $u \geq 0$ and posted vacancies $v \geq 0$. Based on Den Haan, Ramey and Watson (2000), we assume that the flow of successful matches within a period is given by the following constant-returns-to-scale (CRS) matching function:

$$m(u,v) = \frac{uv}{(u^{\chi} + v^{\chi})^{1/\chi}}, \tag{22}$$

where $\chi \geq 0$ is a parameter to be calibrated. The appealing feature of this matching function relative to the Cobb-Douglas specification is that it guarantees that matching probabilities are between zero and one for all values of u and v. Specifically, the job-finding probability $p(\theta)$ and the job-filling probability $q(\theta)$ are, respectively,

$$p(\theta) = (1 + \theta^{-\chi})^{-1/\chi}, \tag{23}$$

$$q(\theta) = (1 + \theta^{\chi})^{-1/\chi}. \tag{24}$$

Next, we turn to the parameters related to frictions in the labor market, (δ, k, χ). We set the job-separation rate δ equal to 2%. Then, we jointly calibrate the unit vacancy cost, k, and the matching technology parameter, χ such that: (i) tightness ratios are equal to one in the steady state;[32] and (ii) job-finding probabilities equal 0.3. This strategy yields $k = 1.2$ and $\chi = 0.5973$.

Bargaining weights We consider two distinct calibrations of the bargaining weights. In the first calibration, we set the bargaining weight's value to be identical across all submarkets. For well-known reasons, such a calibration implies that the wage varies across different submarkets. Such a variation introduces another channel through which individuals with higher UIB are likelier to seek employment on top of the liquidity value of UIB: namely, that the incentives to search are greater due to the higher return from a higher wage.

However, there are two main shortcoming with this approach. First, it is not obvious whether such a channel is operative in our data (we do not observe the wages of the individuals upon rehiring). Second, and perhaps more importantly, recall that our empirical results suggested that there is no associated probability increase in active search occurring due to individuals having had higher past wages. In contrast, our empirical results suggest that the variation in predicted search probabilities arises from variation in UIB. We thus aim to isolate the effects of UIB.

Hence, here, we present a version of the model where the bargaining weights vary across the different submarkets, such that the resulting bargained wage is identical across all submarkets. This has the advantage of isolating the role of the UIB as the sole reason for variation in search probabilities. Moreover, it highlights the role of UIB as a liquidity source.[33] The calibrated values of the bargaining weights lie in the interval $[0.3011, 0.5]$, ranging from a value of $\rho = 0.3011$ for the submarket with the highest replacement rate to $\rho = 0.5$ for the submarket with the lowest replacement rate. These bargaining weights assure that the wage is the same across submarkets that differ in replacement rates.

[32] This is a normalization without loss of generality.

[33] In Appendix D, we consider results from a version of the model where all markets have the same bargaining weight, such that wages differ across submarkets. Importantly, none of the results presented in the body of the paper changes.

Search costs We are left to parametrize the distribution of search costs, which we assume are drawn from a Log-Normal distribution with mean μ_s and variance σ_s^2. To pin down these two values we proceed as follows: recall that equation (21) implicitly determines the search cutoff value. Given a parameterization of the search cost distribution, this search cost cutoff value maps to the cumulative distribution function (CDF) of searchers in each different submarket.

As discussed above, our empirical results imply that variation in predicted search probabilities results from variation in UIB and not from variation in past wages. This is why we choose to have as our benchmark calibration the same wage across submarkets, that differ in terms of UIB amounts. This leads, as in our empirical analysis, to a situation where search probabilities vary solely because of variation in replacement rates.

We thus choose as our calibration targets the estimates reported in Table 3, again noting that the variation in predicted search probabilities emerges from variation in the UIB, and not past wages. We then proceed as follows. We employ a non-linear search algorithm over the parameter space of μ_s and σ_s, calculating for each pair the vector of model-implied CDFs across the different submarkets. The resulting vector is compared with the underlying empirical search probabilities reported in Table 3. We pick the pair that minimizes the sum of deviations between the model-implied CDFs and the estimated search probabilities.

Tax rate For the benchmark economy, and for each of the reforms, we calculate the tax rate resulting in government revenues equaling government expenses on unemployment benefits.

6. Policy Experiments

In this section we use the quantitative model to examine a number of issues about which our identified moments cannot provide a definite answer: (i) quantification of the equilibrium effects of changes in benefit generosity across the distribution of replacement rates; (ii) study how the magnitude of these effects depends on the degree of wage flexibility; (iii) evaluation of the extent of non-linearities in the transmission mechanism of benefit changes to the mass of searchers, job-finding rates conditional on searching, and employment rates.

In addition, it is also of interest to assess if and extent to which the effect of a change in benefit generosity is *non-monotonic* in its size, an issue that our *local* empirical analysis cannot address. In fact, general equilibrium forces can in principle cause the mass of searchers to decline in response to increases in benefit generosity, even if the underlying estimated elasticity is positive. This can arise in instances where reforms in UI benefits are so large that they lead to major reductions in the job-finding rate conditional on searching, making it less attractive to engage in search. For example, consider the extreme case where UIB are so high that the “search-and-matching” market shuts down, i.e., there is no equilibrium with vacancy posting. In such a case, although the UIB are higher, the search probability will collapse to zero. Such general-equilibrium considerations cannot be captured by the reduced-form estimates in our empirical analysis.

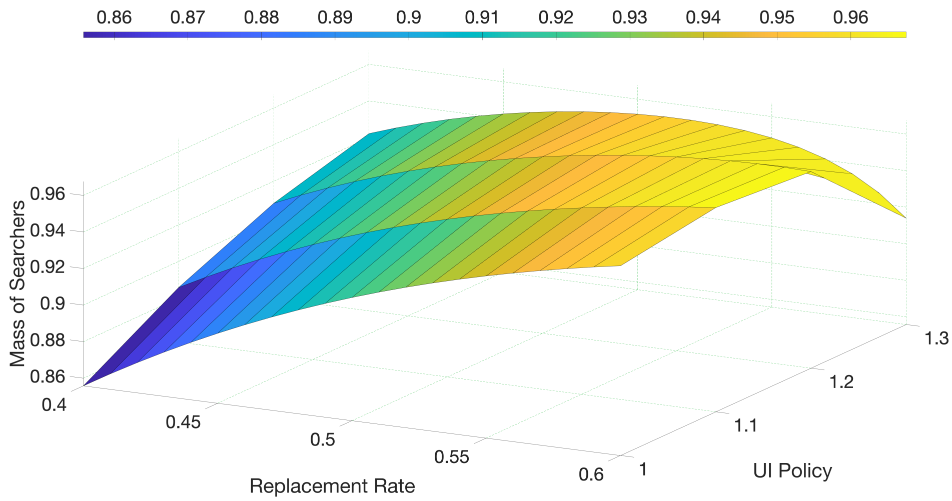
Given the presence of a distribution of replacement rates, we model UI reforms as policies that multiply the vector of replacement rates $\vec{b}$ by a constant factor. Thus, for example, for a reform that prescribes an across-the-board 10% increase in replacement rates, the post-reform replacements rates are equal to the pre-reform rates times the factor 1.1. Overall, we consider reforms ranging from a factor of 1.1. to 1.3, i.e., from 10% to 30% across-the-board increases in replacement rates.

6.1. Mass of Searchers

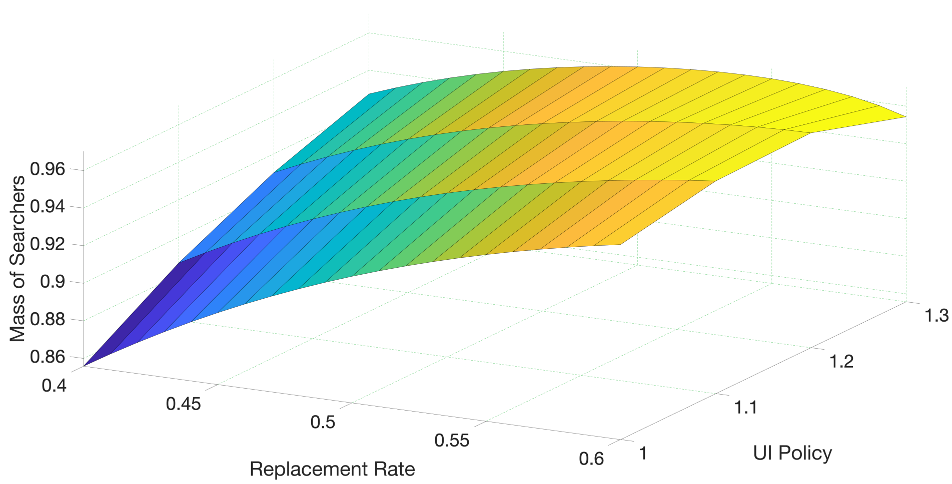
Figures 2a-2c depict the resulting equilibrium mass of searchers for (i) the three different wage mechanisms discussed above, and (ii) different magnitudes of policy reforms. In these figures, as well as in the remaining ones in this section, the x-axis reports the pre-reform replacement rates. On the y-axis, we report the different UI policy factors that multiply the pre-reform replacement rates. The curve at the lower edge of the graph, corresponding to where the UI policy factor equals one, shows the mass of searchers in the benchmark economy prior to the reforms. Note that the benchmark mass of searchers is the result of our matching moment exercise, and hence it is the same in each of the three panels (one for each wage mechanism).

Consider first the case of Nash bargaining in Figure 2a. In this case, for reforms that are not "too big," we find that the mass of searchers increases for all values of pre-reform replacement rates. However, once reforms imply values of replacement rates roughly above 70%, they can lead in fact to a reduction in the mass of searchers. To understand the forces at work, one need to consider the impact of the UIB policy change on the job-finding rates conditional on searching, as depicted in Figures 3a-3c. Under the Nash-bargaining scenario, "big reforms" that push replacement rates to very high levels, significantly lower the job-finding rate (conditional on searching), such that the overall return to engage in active search declines. This happens, because, as is common for the Nash-bargaining wage protocol, the equilibrium wage increases in response to the increase in benefits, as depicted in Figure 4a. Such drops in the job-finding rate negatively affect the return to searching, which results in a smaller mass of unemployed individuals engaging in actual job

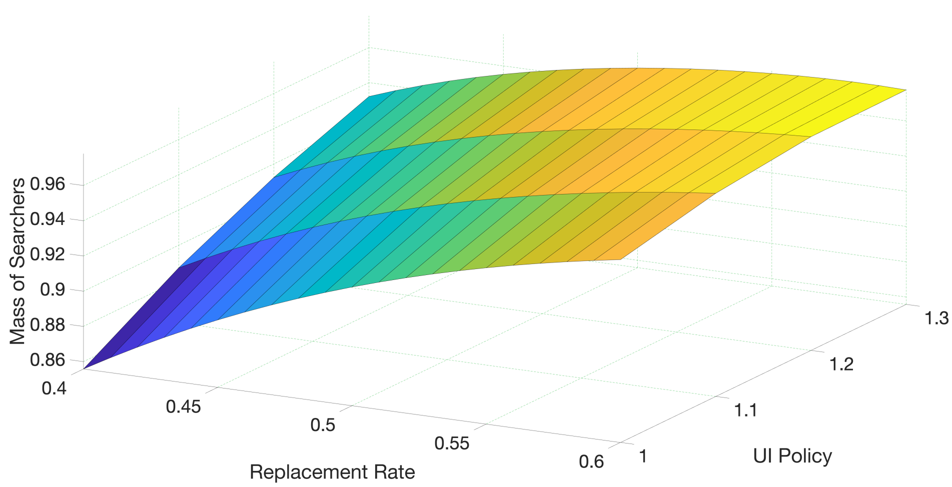
Figure 2: Relation between UI Benefits and Fraction of Searchers



(a) Nash Wages



(b) Semi-Flexible Wages



(c) Sticky Wages

search.

In the case of sticky wages, instead, reforms that increase replacement rates across the board, leave wages unchanged by construction. By the free-entry condition for job vacancy posting, this implies that job-finding rates conditional on searching are unaffected by the reforms, too. As such, the sole effect of higher benefits is to provide "liquidity" for the unemployed to afford the monetary search cost. This, unambiguously, explains why higher benefits lead to a greater search likelihood for all values of pre-reform replacement rates, as depicted in Figure 2c.

The case of the semi-flexible wages, which was restricted to match the reported elasticity of the job-finding rate to benefits as in Chetty (2008), naturally lies in between the two extremes of Nash-bargaining and sticky wages. In a nutshell, this model exhibits an increase in the search likelihood for almost all values of replacement rates, besides, again, those that cross a threshold of about 70%. Under semi-flexible wages, the job-finding rate conditional on searching does not exhibit the precipitous fall that it has under Nash-bargaining. Dampening the decline in the job-finding rate increases the relative return to engage in active search.

To sum, an important lesson from the GE model is that UI policy reforms can in fact reduce the mass of searchers if they result in increasing replacement rates above a certain threshold. For relatively modest reforms, benefit changes lead to an increase in the mass of active searchers in the economy. For example, for the semi-flexible wage case, we find that the *average* benefit recipient would increase her search likelihood by 1 percentage point, in the case of the smallest benefit reform, and 4.3 percentage points in the case of the biggest benefit reform we consider. Yet, such big reforms would lead those who would be entitled to very high replacement rates to exhibit a fall in their search likelihood; for example, for the same semi-flexible wage case we find the highest benefit recipient would exhibit a fall of about 0.5 percentage points in her search likelihood.

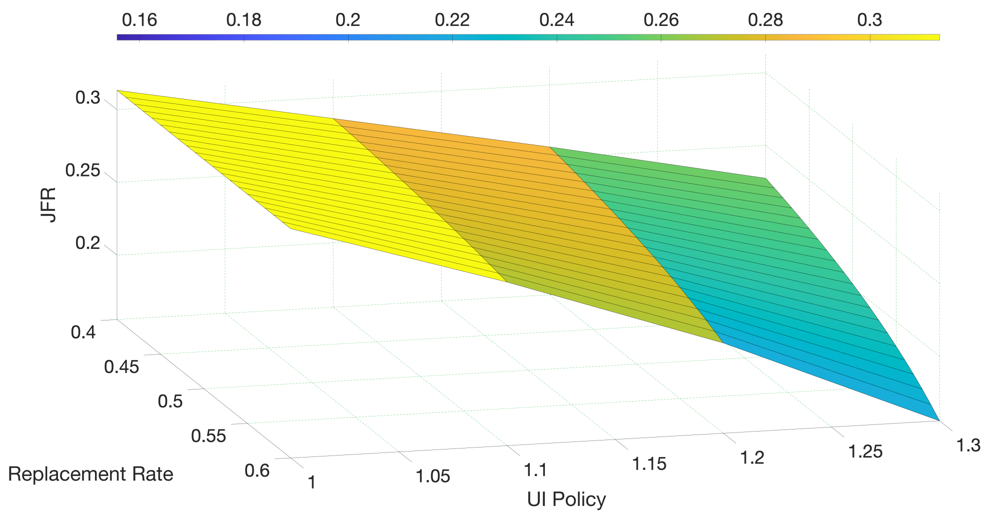
6.2. Employment Rate

In the steady state of the model, the employment rate of individuals with replacement rate b is given by

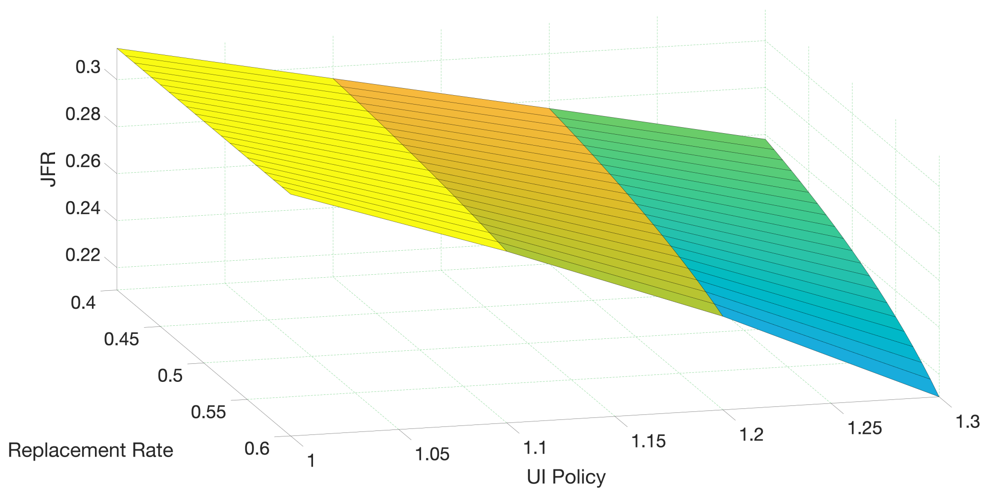
$$E = \frac{\Omega(b)p(b)}{\delta + \Omega(b)p(b)}, \tag{25}$$

where $\Omega(b)$ is the fraction of individuals engaged in active search, $p(b)$ is the likelihood of finding a job *conditional* on searching, δ is the exit rate from employment, or job-destruction rate, and U

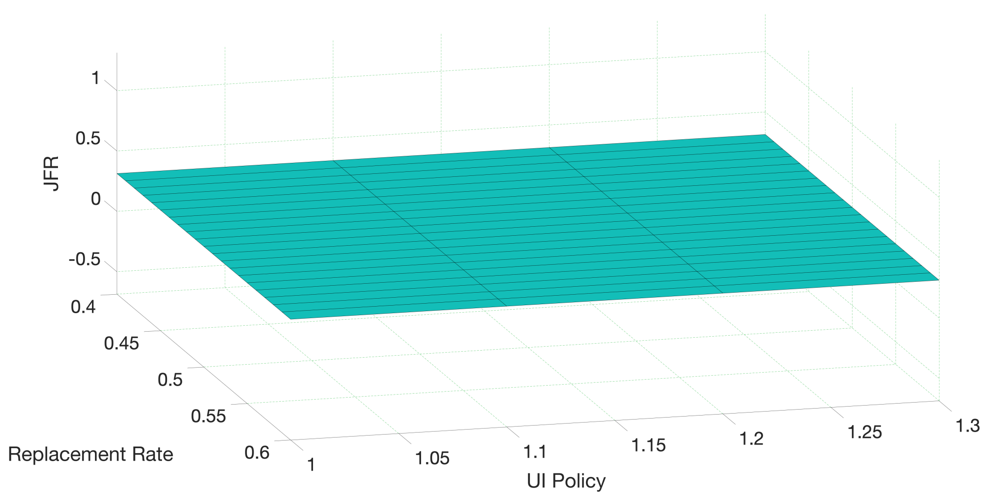
Figure 3: Relation between UI Benefits and Job-Finding Rate Conditional on Searching



(a) Nash Wages

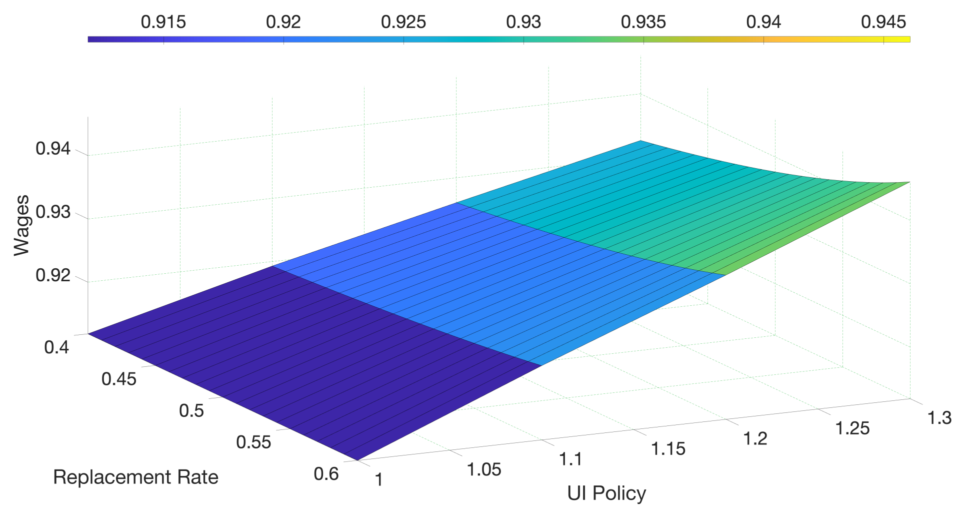


(b) Semi-Flexible Wages

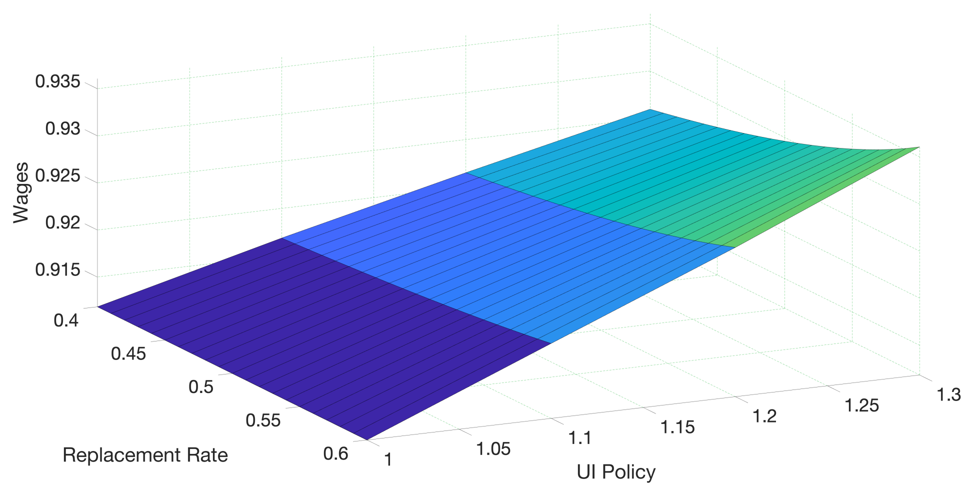


(c) Sticky Wages

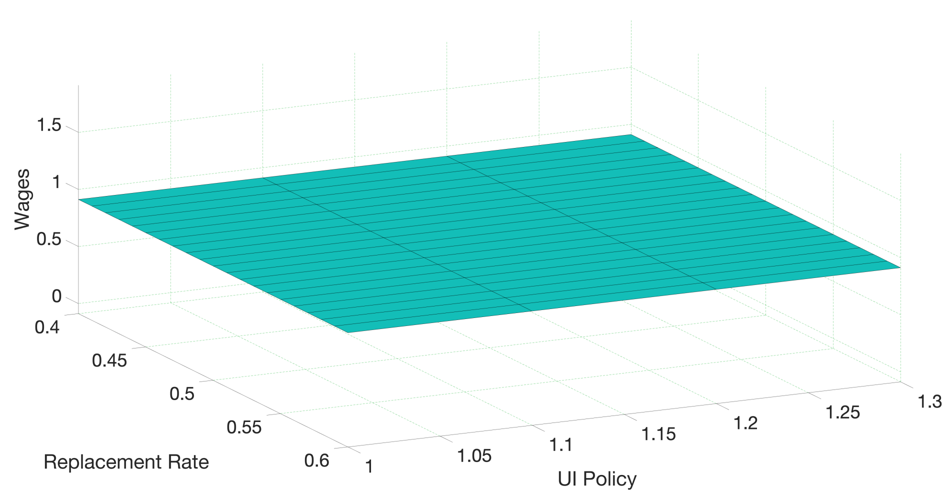
Figure 4: Relation between UI Benefits and Wages



(a) Nash Wages



(b) Semi-Flexible Wages



(c) Sticky Wages

denotes the unemployment rate.[34] A log-linearized version of (25) yields

$$\widehat{E} = \left(\frac{\Omega'(b)b^*}{\Omega(b)} + \frac{p'(b)b^*}{p(b)} \right) U^* \widehat{b}, \tag{26}$$

where, for comparison, absent an active search margin the log-linearized expression is given by

$$\widehat{E} = \left[\frac{p'(b)b^*}{p(b)} \right] U^* \widehat{b}. \tag{27}$$

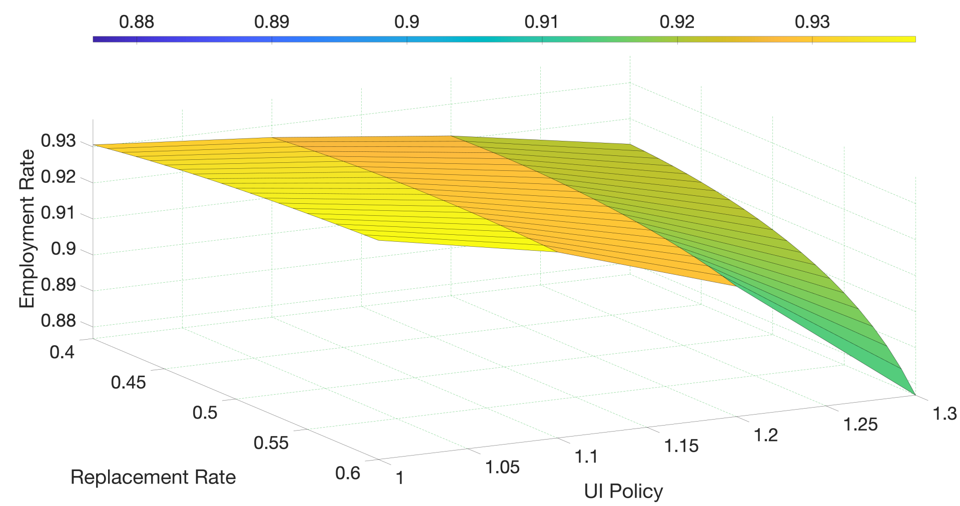
Hence, given our empirical finding that $\Omega'(b)b^*/\Omega(b) > 0$, the disincentive effect of UIB on the employment rate, $p'(b)b^*/p(b) < 0$, is mitigated. Ceteris paribus, any increase in the mass of searchers leads to a corresponding uptick in the employment rate, which counteracts the disincentive effect of UI benefits conditional on searching.

Figures 5a-5c depict the employment rate for the different UIB policy changes: as before the curve at the lower edge of the graph, corresponding to where the UIB policy axis equals one, is identical in each of the three panels and illustrates the employment rate in the benchmark economy prior to any policy reform. First, naturally, for the sticky-wage equilibrium, the employment rate rises for all reforms and for all values of the pre-reform replacement rates; again, this stems from the fact that the job-finding rate conditional on searching does not change (Figure 3c), while the fraction of searchers increases (Figure 2c). However, as Figures 5a-5b show, in the Nash-bargaining and semi-flexible wage case, the employment rate always falls, more so as the reforms become more generous. This stems from the job-finding rate unambiguously falling.

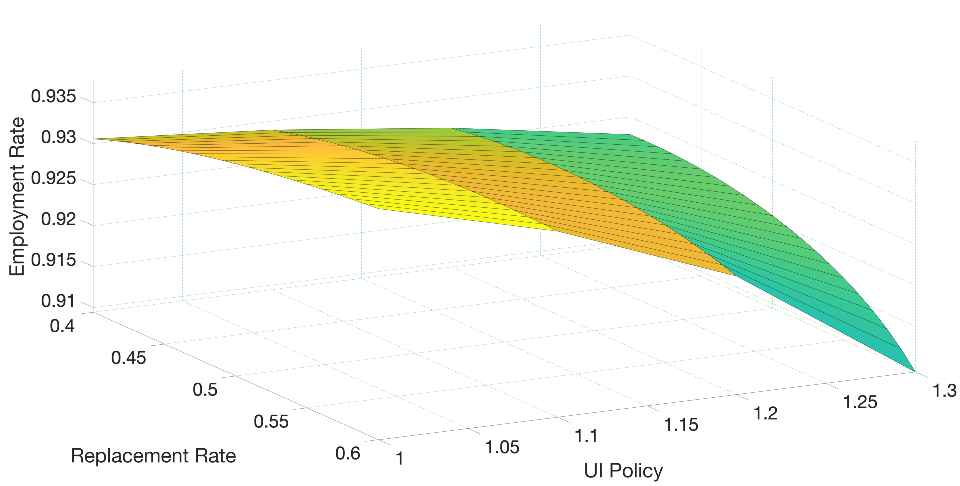
What is the quantitative contribution of an active search on the employment rate? To gauge the effect, we compare the employment rate change implied by the reforms in the baseline economy with search with a counterfactual economy without an active search margin, in which all adjustment comes form changes in the job-finding rate. Figure 6 compares the change in the employment rate relative to its value prior to any reform for the three different wage settings and reform sizes. Consider the semi-flexible wage economy, which is depicted in the second row of Figure 6. In this case, for almost all scenarios the employment rate *falls by less* in our baseline economy than in the counterfactual economy without a search margin. This is because the search likelihood increases in the baseline economy which counteracts the fall in the job-finding rate conditional on search.

[34] Consistent with our data, we classify as unemployed those individuals who do not engage in active search but receive benefits. As shown in Table 1, in our data, a nontrivial share of unemployed individuals does not meet the requirement of active search.

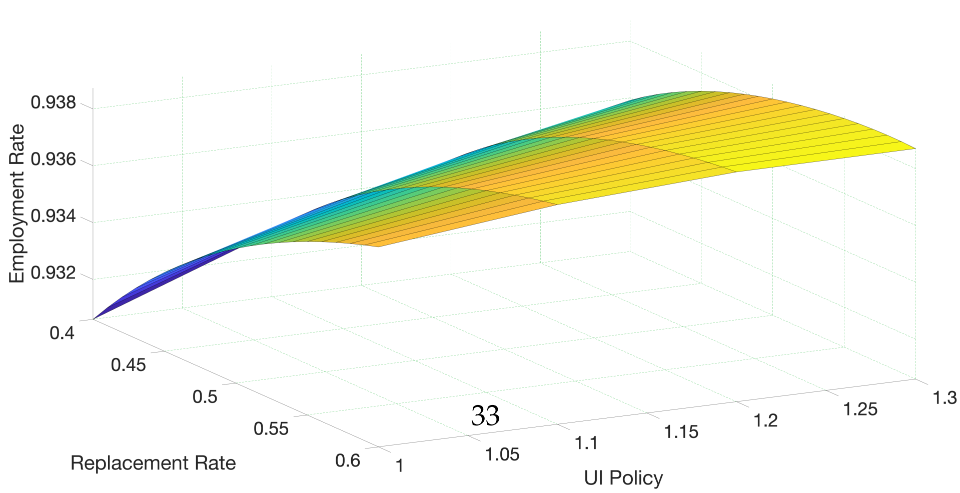
Figure 5: Relation between UI Benefits and Employment Rate



(a) Nash Wages

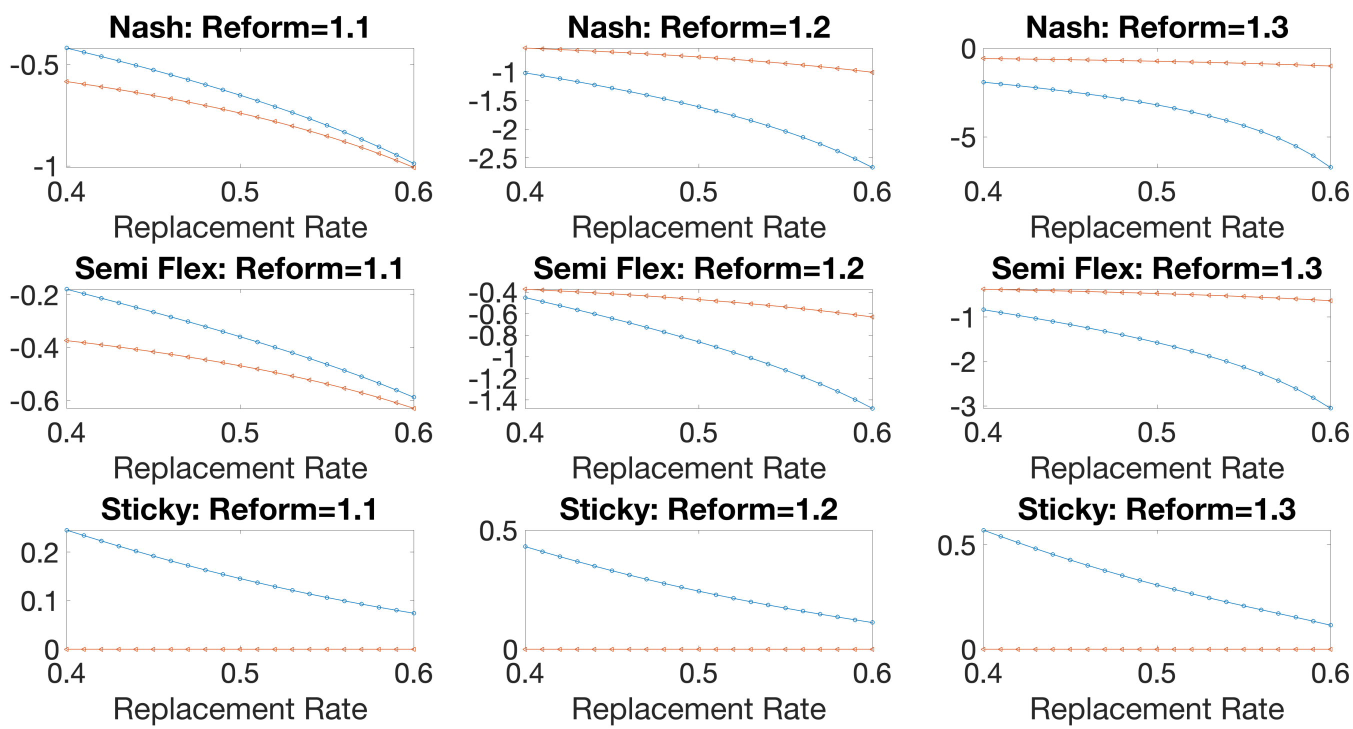


(b) Semi-Flexible Wages



(c) Sticky Wages

Figure 6: Role of Active Search Margin



Notes: The panels depict the percent (%) change in the employment rate (y-axis) by pre-reform replacement rates (x-axis), across the three different wage mechanisms (columns), and different UIB reforms (rows). Lines depicted in blue with circles depict the employment rate change in our baseline economy with active search, while lines depicted in red with triangles depict the corresponding change in the counterfactual economy without search.

6.3. Unconditional Job-Finding Rate

What is the resulting effect on the *unconditional* job-finding rate? In our model, this is the product of the mass of searchers and the job-finding rate conditional on search:

$$P = \Omega(b)p(b), \tag{28}$$

Log-linearization of (28) yields a "generalized" elasticity of the job-finding rate to benefits,

$$\daleth \equiv \frac{\widehat{P}}{\widehat{b}} = \frac{\Omega'(b^*)b^*}{\Omega(b^*)} + \frac{p'(b)b^*}{p(b^*)}. \tag{29}$$

Estimating the elasticity of the job-finding rate with respect to benefits is the focus of many papers in the literature, which typically finds a negative elasticity, i.e. $\daleth < 0$.[35]

The expression in (29) shows that the generalized elasticity includes two different elasticities: (i) the elasticity of the likelihood of job search, $\Omega'(b^*)b^*/\Omega(b^*)$; and (ii) the elasticity of the job-finding probability conditional on engaging in active search, $p'(b^*)b^*/p(b^*)$. Thus, the effects of changes in UIB on the job-finding rate, P, operate through two channels. To begin, everything else equal, more generous UIB can induce more individuals to engage in search, as implied by our empirical estimates of $\Omega'(b^*)b^*/\Omega(b^*) > 0$. In the context of our model we refer to this channel as the "liquidity effect" of UI, in reference to the fact that more generous benefits allow individuals to afford the monetary search cost. Previous literature has abstracted from this elasticity, since direct information on active search has been generally of poor quality or missing altogether. The second margin, which we refer to as the "disincentive effect" of UIB.[36] This is the channel whereby an increase in UIB generosity may induce the exit rate from unemployment to fall given the fact that $p(b)$ is decreasing in b.[37]

[35] The literature that studies the effects of UIB on labor market outcomes is extensive. It can be largely divided into two groups. The first uses detailed micro data to study the extent to which the generosity of UIB affects *unemployment duration* at the level of individuals. While the exact magnitudes of the effects vary by study, a consensus view has emerged that: a higher replacement rate increases unemployment duration (see, e.g., Carling, Holmlund and Vejsiu (2001), Røed and Zhang (2002), Lalive, Van Ours and Zweimüller (2006)) and that the exit rate from unemployment spikes at the time benefits expire (see, e.g., Moffitt and Nicholson (1982), Moffitt (1985), Grossman (1989), Katz and Meyer (1990*a*,*b*), Meyer (1990), Card and Levine (2000), Lalive and Zweimüller (2004), Lalive, Van Ours and Zweimüller (2006), Landais (2015), Schmieder, Von Wachter and Bender (2012), and Johnston and Mas (2018)). These findings have typically been interpreted as evidence of the disincentive effect of UI (see, e.g., Krueger and Meyer (2002), for a survey article, and Feldstein (2005)).

[36] The literature also uses the term "moral hazard" in reference to the adverse incentive effect of UI both on individual search and on job acceptance decisions.

[37] What are the implications of our local empirical finding that $\Omega'(b^*)b^*/\Omega(b^*) > 0$ for the measurement of the disincentive effect of UIB? It follows that the disincentive effect of UIB estimated in the literature is, in fact, a lower

As discussed above, our empirical result cannot be used, by itself, for policy analysis. As such, Figures 7a-7c depict the implications of the reforms for the unconditional job finding rate, which is the product of the measure of searchers, depicted in Figures 2a-2c, and the job-finding rate conditional on search, depicted in Figures 3a-3c. Perhaps not surprisingly, Figures 7a-7c show the full extent of the non-linearities embodied in the model. For the cases where the measure of searchers increases, this act to mitigate the fall in the unconditional job-finding rate. However, once the economy enters into the region in which the search likelihood falls, the unconditional job-finding rate takes a nose dive.

6.4. Discussion

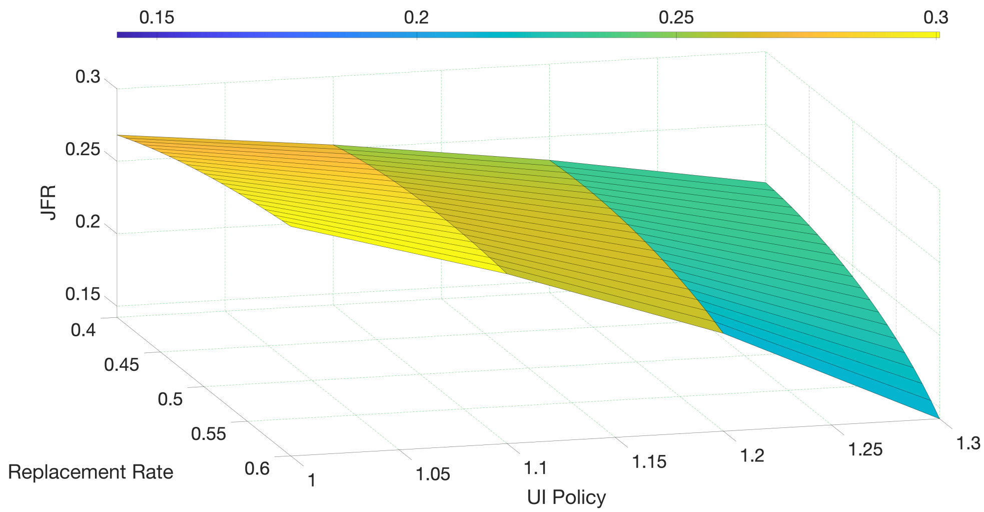
Several important insights emerge from the policy experiments. First, UI benefit reforms implemented under sticky wages have no effect on wages or job-finding rates. The only GE equilibrium channel at work in this version of the model is the required change in the tax rate to balance government expenditures on benefits. Overall, for the type of reforms considered, the liquidity provided through more generous benefits increases the mass of searchers.

Second, the picture changes in the case of Nash-bargained or semi-flexible wages, which are in-between the Nash and sticky-wage economies. Two opposing effects battle. On the one hand, the *partial-equilibrium* liquidity effect that more generous benefits induce an increase in the mass of searchers. On the other hand, increased benefits strengthen the bargaining position of unemployed individuals, leading to lower job-finding rates, conditional on searching. As the analysis above suggests, with respect to the mass of searchers, the liquidity effect dominates over the reduction in job-finding rates for "modest reforms," i.e., for reforms whose implied replacement rates remain below 70%. Below that threshold, though the mass of searchers increases, the employment rate falls, albeit by less than it would have fallen without the increase in the fraction of individuals searching in the economy. Yet, for more "extreme reforms," that raise replacement rates above that threshold, the disincentive effect of increased benefits on the job-finding rate overpowers the enhanced benefits from liquidity. These reforms result in a decline in the search probability and in the employment rate, leading the exit rate from unemployment to exhibit a steep fall.

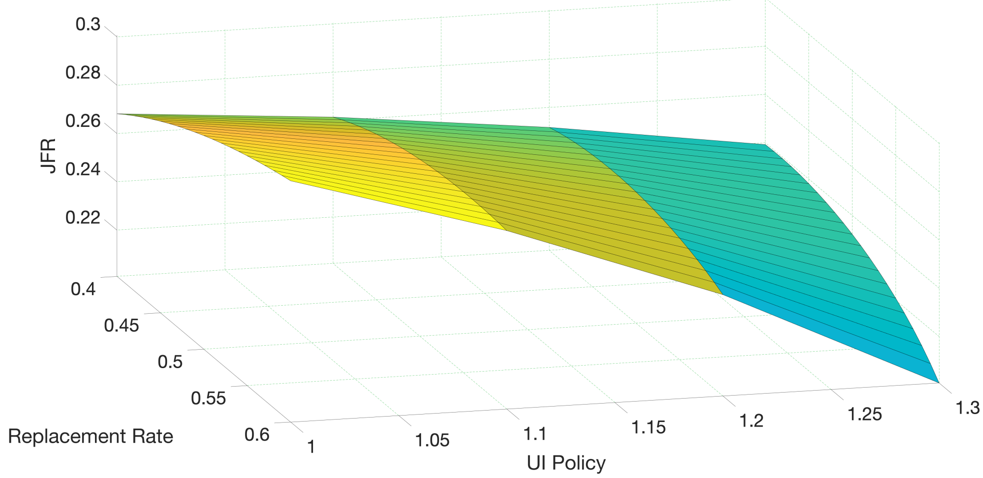
Third, we note the importance of considering the fiscal side of these reforms for the evaluation of the impact they have on the economy. Recall that as part of our general-equilibrium analysis we

bound of the true effect. To see this, note that equation (29) implies that $\frac{p'(b)b^*}{p(b^*)} = \daleth - \frac{\Omega'(b^*)b^*}{\Omega(b^*)}$. Our estimate of the search elasticity $\Omega'(b^*)b^*/\Omega(b^*)$ of about 0.09 implies that researchers can pick their favorite value of $\daleth$ and recover a new, lower (i.e., more negative) value for the disincentive effect of UIB.

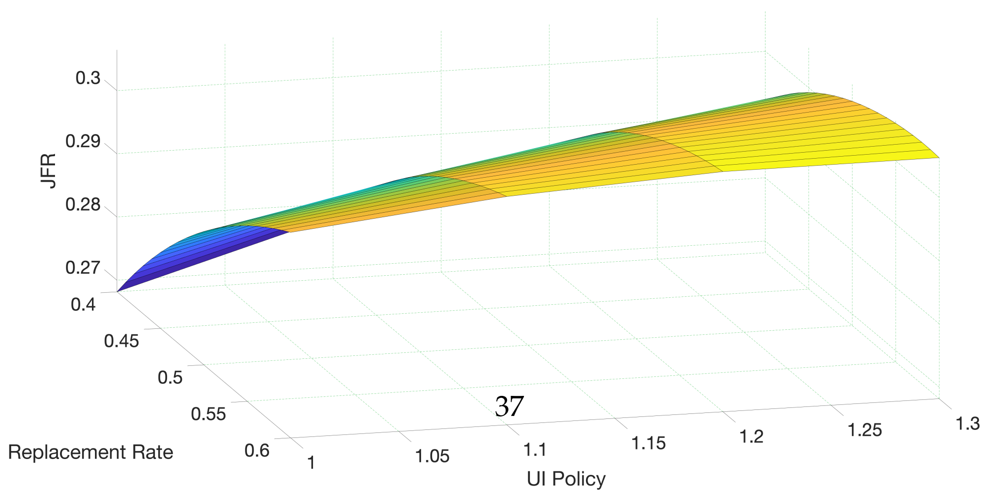
Figure 7: Relation between UI Benefits and Job-Finding Rate



(a) Nash Wages



(b) Semi-Flexible Wages



(c) Sticky Wages

look for the tax rate needed to fund the additional government expenses on UI benefits implied by the reforms. In our economy, the tax rate always increases with the generosity of benefits which reduces work incentives. Appendix C formally shows this by comparing the response of the different variables of interest in our economies vis-à-vis economies where the tax rate is not changed (and thus the government budget constraint is not cleared). Naturally, absent the required hike in the tax rate, all UI reforms end up with more "favorable" labor-market outcomes.

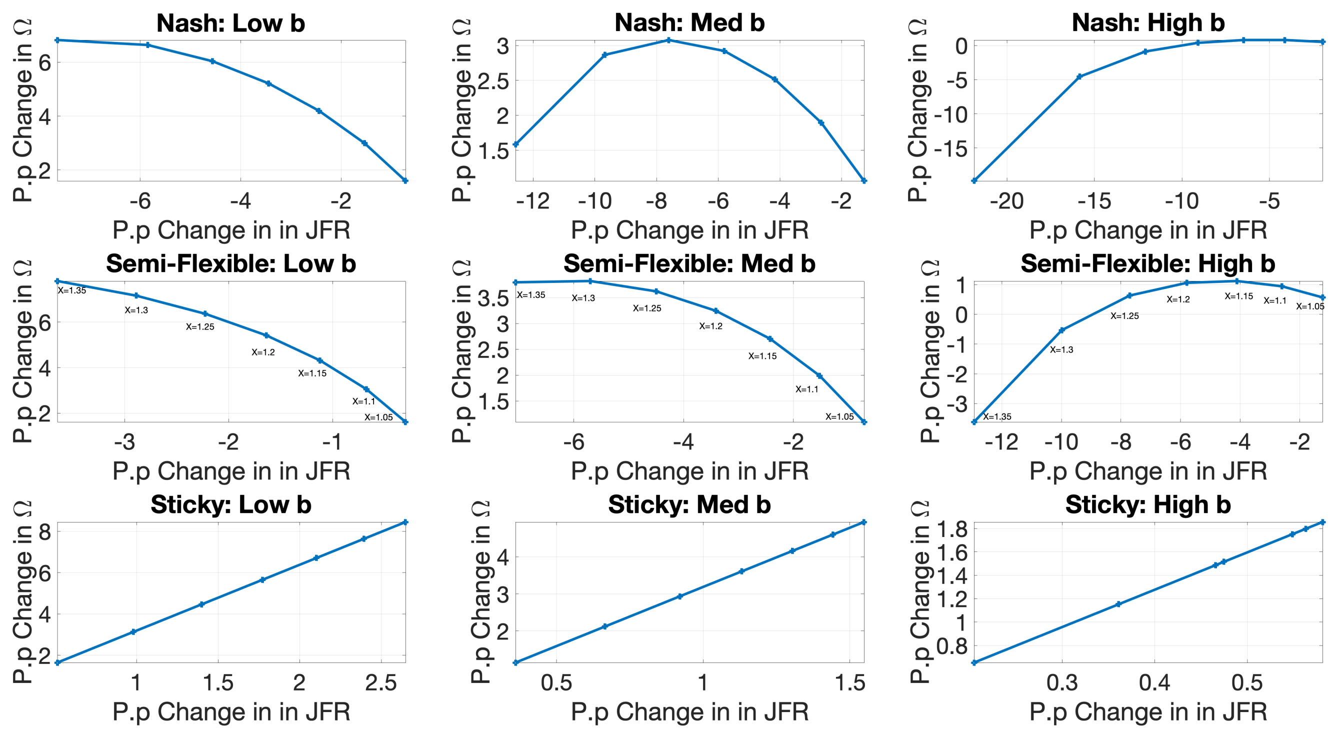
Figure 8 summarizes the tradeoffs between the increase in the mass of searchers and the fall in the exit rate from unemployment across the different wage settings and for individuals located at different points of the pre-reform distribution of replacement rate. For concreteness, consider the middle row of the semi-flexible wage economy and the first column which corresponds to individuals with the lowest pre-reform replacement rate. As the figure shows, the tradeoff between a fall in the exit rate and the increase in the measure of searchers is visible. As the size of the reform increases (moving northwest), the exit rate declines further and further while the measure of searchers increases. For these individuals, the reform does not result in replacement rates that cross the threshold above which the measure of searchers starts to fall. In contrast, consider the last column which corresponds to individuals with the maximum pre-reform replacement rate. For this group of individuals, there are reforms for which both the exit rate and the mass of searchers fall. Note, for sake of comparison, that in the Nash-bargaining scenario (first row of Figure 8), for the same individuals, the fall in the mass of searchers occurs for even smaller reforms. Hence, an important message is that the effects of changes in UIB on job search are generally *non-monotonic*, such that the sign of the comparative statics with respect to the measure of searchers may even flip depending on the magnitude of the change in UIB prescribed by the reform.

Figure 8 highlights the tradeoffs faced by a policymaker. UI benefit reforms can in fact lead to an increase in the measure of unemployed engaged in active search. Such an increase would counteract the usual disincentive effect of increased benefits on the exit rate from unemployment. However, large increases in UIB generosity could in fact be counterproductive as they would result in a drop in the measure of searchers on top of the usual disincentive effect of benefit increases. Hence, one important implication of the model is that the estimated effects in our empirical analysis are not necessarily informative about the effects of large reforms, which naturally set general equilibrium forces in motion. A policymaker considering solely our empirical estimates would fail to recognize the detrimental effect of large changes in the generosity of the unemployment insurance system.

Overall, our policy analysis findings relate to the recent important research that focuses on the *equilibrium* response of wages, job creation, and labor market tightness. This literature highlights the general-equilibrium effects of UIB. Perhaps not surprisingly given the challenge task of identifying these effects, different researchers have arrived at different results. Hagedorn et al. (2013) estimate a large and positive macro elasticity of unemployment with respect to a change in UIB generosity in the United States. They do so by comparing counties that border states with different potential benefit durations, finding that benefit extensions raise equilibrium wages and lead to a sharp reduction in vacancy posting and employment. Moreover, Hagedorn, Manovskii and Mitman (2015) study what happens when benefit extensions are eliminated nationwide, which occurred in the U.S. in December of 2013 after the U.S. congress failed to reauthorize the benefit extensions introduced during the Great Recession. They find that reducing the benefit duration boosted aggregate employment considerably. Consistent with these results, Johnston and Mas (2018) look at the unexpected cut in potential benefit duration that took place in Missouri in April 2011. They discover a significant positive effect on job creation. In contrast, Chodorow-Reich, Coglianese and Karabarbounis (2018) exploit cross-state variation in UIB extensions caused by measurement error in within-state unemployment rates. These errors stem from data revisions to the actual measured unemployment rate and imply that two states with the same revised unemployment rate may end up having different benefit durations solely because their real-time measured unemployment rates differed. This approach identified a small or even negative effect of benefit extensions on unemployment. Similarly, Boone et al. (2016) find no evidence that UI benefit extensions during the Great Recessions substantially affected county-level employment.[38]

[38]See Dieterle, Bartalotti and Brummet (2020) for recent work casting doubts on the research design that uses cross-border variation to identify the macro effects of UI benefit extensions.

Figure 8: Policy Tradeoff Frontier: UI Benefits, Mass of Searchers, and Job-Finding Rates



Notes: The panels depict the percentage point (p.p.) change in the job-finding rate (x-axis) and mass of searchers (y-axis), across the three different wage mechanisms (columns), and different values of pre-reform replacement rates (rows). Each marker specifies the policy factor that multiplies the pre-reform replacement rates. That is, post-reform replacement rates are equal to X times pre-reform replacement rates with $X \in \{1.05, 1.1, 1.15, 1.2, 1.25, 1.3, 1.35\}$.

7. Conclusion

We use a unique and rich dataset that enables us to estimate the effect of unemployment insurance generosity on the likelihood of an unemployed individual engaging in active job search. Our identification leverages plausible exogenous variation in benefits due to the fact that in most U.S. states benefit amounts are determined based on the earnings in the best quarter of the previous year. Controlling for past wages, standard demographic characteristics, as well as the industry and occupation of the individual before the unemployment spell, our estimates suggest a positive and statistically significant effect of UIB on the likelihood of job search for most deciles of the past wages distribution.

To rationalize these findings, we provide a simple non-parametric theoretical framework that points to a monetary cost of job search as a key driver of our results. We build on this insight and develop a quantitative search-and-matching, heterogeneous-agent, general equilibrium model with costly search. We then use the model as a laboratory to evaluate the effects of different changes in the unemployment insurance system.

In the model, there is a trade-off that is relevant for the evaluation of policy reforms. Everything else equal, more generous benefits induce more unemployment individuals to search. This is the "liquidity effect" of UIB in that it allows individuals to afford the monetary cost of search. However, by improving the bargaining position of the unemployed, higher benefits lead to higher wages, which in turn depresses vacancy posting and thereby the probability of finding a job conditional on searching. We refer to this as "disincentive effect" of UIB in that by adversely affecting the job finding probability, it can dissuade individuals from actually engaging in job search, implying the possibility of non-monotonic effects of benefit changes on the fraction of unemployed individuals actively looking for employment.

Notably, for small reforms, the positive response of the search margin mitigates the negative disincentive effect on the employment rate. For large reforms, instead, the disincentive effect can be strong enough so that the reduction in the fraction of individuals searching magnifies the negative effects on the employment rate. Overall our results suggest that the policy maker faces a tradeoff that has not been discussed before when considering unemployment insurance reforms – that between the increase in the measure of unemployed engaged in active search which comes at the cost of a fall in the exit rate from unemployment.

Altogether, the results in this paper highlight the importance of direct measurement of monetary search costs, information about which is almost non-existent. Concretely, standard surveys of the labor market could add questions aimed at gauging the extent, as well as the type, of real costs incurred by job seekers. Our empirical and theoretical results suggest that measuring these costs is essential to bringing about any well-designed reform of the unemployment insurance system.

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A. Appendix: Data Source and Variables' Construction

A.1. Dataset

Dataset construction The underlying row data has 635,940 observations covering the years 1989-2006. We remove 171,500 observations of individuals who for different reasons are not required to engage in search and are left with 438,980 observations. We then remove observations that belong to states that do not use the HQ system and lose 257,253 observations and are left with 181,727 observations. We remove 21,382 observations for which we have missing information (such as information about occupations and industries worked, HQ, education, maximum benefit amount in the state year, recall status, weeks left, age, race) and are left with 160,345 individuals. In order to be able to estimate the effects of UIB on the likelihood of search we need to have a minimal number of non-searchers since in their absence it would create difficulties for inference due to very small probability events. As such, we only use states which use the HQ system and have more than 600 observations of individuals who were required to search in order to be eligible for UIB but who did not engage in active search. This restriction leaves us with a sample size of 65,556 observations. Our HQ states include Arizona, Indiana, Minnesota, North Carolina, Nevada, Virginia, and Washington.[39] We also experiment with less stringent minimum number of non-searchers per state which increases our sample size and find our results to be generally robust to these alternative specifications.

BPW and HQ Because BPW in the data are censored at $100,000, our analysis centers on the subpopulation of individuals whose BPW is below this threshold. As we discuss in the text, we carry out the analysis for subpopulations defined by the deciles of the BPW distribution and place no restrictions across these quantiles as to the impact of UIB, BPW, and other covariates on job search. Thus, our results are unaffected by the choice to focus on individuals earning at most $100,000 in the base period, but pertain only to this subpopulation. With respect to the HQ variable we note that our data only includes information regarding the single highest quarter during the year prior to the unemployment spell.

Search Each payment error in the BAM data is assigned a code. Our search variable is based on a lack of eligibility error due to active work search.

Two digit occupations & SOC codes 11 Management Occupations, 13 Business and Financial Operations Occupations,15 Computer and Mathematical Occupations, 17 Architecture and Engineering Occupations, 19 Life, Physical, and Social Science Occupations, 21 Community and Social

[39]For Washington we exclude the year 2005 since in that year Washington did not have the HQ system.

Services Occupations, 23 Legal Occupations, 25 Education, Training, and Library Occupations, 27 Arts, Design, Entertainment, Sports, and Media Occupations, 29 Healthcare Practitioners and Technical Occupations, 31 Healthcare Support Occupations, 33 Protective Service Occupations, 35 Food Preparation and Serving Related Occupations, 37 Building and Grounds Cleaning and Maintenance Occupations, 39 Personal Care and Service Occupations, 41 Sales and Related Occupations, 43 Office and Administrative Support Occupations, 45 Farming, Fishing, and Forestry Occupations, 47 Construction and Extraction Occupations, 49 Installation, Maintenance, and Repair Occupations, 51 Production Occupations, 53 Transportation and Material Moving Occupations, 55 Military Specific Occupations.

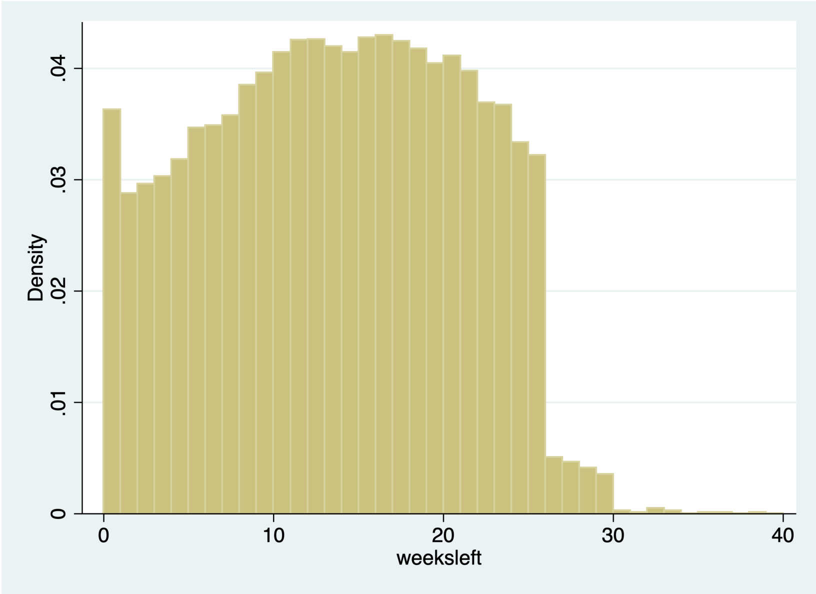
Two digit industries & SOC codes 11 Agriculture, Forestry, Fishing, Hunting, 21 Mining, 22 Utilities, 23 Construction, 31-33 Manufacturing, 42 Wholesale Trade, 44-45 Retail Trade, 48-49 Transportation and Warehousing, 51 Information, 52 Finance and Insurance, 53 Real Estate, Rental and Leasing, 54 Professional, Scientific, and Technical Services, 55 Management of Companies and Enterprises, 56 Administrative Support, Waste Management and Remediation Services, 61 Education Services, 62 Health Care and Social Assistance, 71 Arts, Entertainment and Recreation, 72 Accommodation and Food Services, 81 Other Services (except Public Administration), 92 Public Administration.

Table A1: OLS Regressions of HQ Wages for each BPW Decile Subsample

Decile	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Male	0.0213***	0.0340***	0.0419***	0.0497***	0.0477***	0.0363***	0.0458***	0.0412***	0.0232*	-0.0656***
	(0.00158)	(0.00782)	(0.00289)	(0.00649)	(0.00249)	(0.00373)	(0.00857)	(0.00521)	(0.00995)	(0.0173)
Age	0.00223**	0.00268***	0.00472***	0.00415***	0.00508***	0.00608**	0.00606**	0.00573***	0.00135	-0.00803
	(0.000848)	(0.000719)	(0.000778)	(0.000526)	(0.00129)	(0.00199)	(0.00178)	(0.00123)	(0.00193)	(0.00924)
Age^2	-0.0000299**	-0.0000326**	-0.0000558***	-0.0000444***	-0.0000486**	-0.0000595**	-0.0000581**	-0.0000488**	-0.00000343	0.0000790
	(0.00000910)	(0.00000932)	(0.00000920)	(0.00000649)	(0.0000155)	(0.0000224)	(0.0000200)	(0.0000140)	(0.0000234)	(0.0000979)
Weeks left	-0.00472***	-0.00585***	-0.00542***	-0.00492***	-0.00433***	-0.00347***	-0.00210**	-0.00102	-0.00103	-0.00177
	(0.000451)	(0.000447)	(0.000372)	(0.000519)	(0.000656)	(0.000805)	(0.000672)	(0.000626)	(0.000828)	(0.00134)
Recall	0.00617	0.0204**	0.0284**	0.0505***	0.0690***	0.0889***	0.104***	0.0956**	0.110***	0.138**
	(0.00512)	(0.00814)	(0.0111)	(0.00629)	(0.0151)	(0.0208)	(0.0233)	(0.0267)	(0.0159)	(0.0380)
Black	-0.00195	0.000153	-0.0167**	-0.0132*	-0.0153*	-0.00848	-0.00543	-0.0142*	-0.00938	0.00926
	(0.00173)	(0.00569)	(0.00483)	(0.00612)	(0.00764)	(0.00647)	(0.00503)	(0.00704)	(0.00785)	(0.0381)
Hispanic	0.00549	0.00186	-0.0101	-0.0201	-0.0383**	-0.0247*	-0.0133	-0.0195	0.00857	0.0333
	(0.00350)	(0.0135)	(0.0125)	(0.0105)	(0.0128)	(0.0117)	(0.0119)	(0.0157)	(0.0209)	(0.0378)
Asian	0.0178	-0.00472	-0.0427	0.0140	-0.00581	-0.0146	0.00829	0.000228	0.0511	-0.0380
	(0.0160)	(0.00901)	(0.0220)	(0.0326)	(0.0224)	(0.0163)	(0.0722)	(0.0462)	(0.0709)	(0.0893)
Indian	-0.00262	0.0116	0.00771	-0.00713	0.0247	0.0123	0.0408	0.0378	-0.0530**	-0.0748
	(0.00660)	(0.00956)	(0.00991)	(0.0120)	(0.0275)	(0.0190)	(0.0314)	(0.0305)	(0.0170)	(0.0887)
HS	0.00424	0.00716	0.0163**	0.00765	0.0184**	0.00648	0.0143**	-0.00774	0.0108	0.0174
	(0.00367)	(0.00766)	(0.00486)	(0.00509)	(0.00698)	(0.00669)	(0.00486)	(0.00630)	(0.00999)	(0.0348)
SCAC	0.0110***	0.0273***	0.0372***	0.0321***	0.0365***	0.0220**	0.0269***	0.00546	0.00790	0.0198
	(0.00237)	(0.00672)	(0.00621)	(0.00602)	(0.00732)	(0.00772)	(0.00367)	(0.0111)	(0.0104)	(0.0350)
COL	0.0295**	0.0743***	0.0802***	0.0969***	0.106***	0.0774***	0.0893***	0.0645**	0.0316	-0.0304
	(0.0102)	(0.0149)	(0.00695)	(0.0111)	(0.0176)	(0.0150)	(0.0118)	(0.0190)	(0.0173)	(0.0334)
Observations	5545	5468	5485	5470	5458	5500	5483	5468	5488	5415
R^2	0.464	0.348	0.352	0.333	0.336	0.341	0.369	0.368	0.369	0.607

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Distribution of Weeks Left



Notes: The figure shows the distribution of weeks left by increments of 1 week.

Table A2: Regressions with $log(UIB)$ and $log(\text{Monthly Wage})$

Decile	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
log UIB	0.00114	0.343***	0.389***	0.523**	0.598*	0.693**	0.974**	0.804*	0.290	0.0740
	(0.127)	(0.0956)	(0.137)	(0.222)	(0.316)	(0.308)	(0.418)	(0.415)	(0.380)	(0.202)
log Monthly Wage	0.0103	-0.546	-0.854	-1.230	-1.198*	-0.724	-1.625***	-0.811**	0.0840	0.118
	(0.103)	(0.333)	(0.669)	(0.753)	(0.611)	(0.883)	(0.544)	(0.371)	(0.320)	(0.116)
Male	0.0383	-0.0615	0.00299	-0.00553	-0.0509	-0.0118	-0.0993	-0.0201	-0.00449	-0.0421
	(0.0353)	(0.0499)	(0.0571)	(0.0480)	(0.0872)	(0.0303)	(0.0612)	(0.0641)	(0.0428)	(0.0948)
Age	0.0220	0.0247***	0.0117	0.0209*	0.0277*	0.0537***	0.0322**	0.0253**	0.0295	0.0144
	(0.0136)	(0.00906)	(0.00788)	(0.0108)	(0.0150)	(0.0120)	(0.0141)	(0.0110)	(0.0211)	(0.0290)
Age^2	-0.000193	-0.000275***	-0.0000821	-0.000202	-0.000250	-0.000579***	-0.000333**	-0.000258*	-0.000320	-0.000216
	(0.000154)	(0.000103)	(0.0000901)	(0.000136)	(0.000184)	(0.000137)	(0.000161)	(0.000133)	(0.000236)	(0.000317)
High School	0.128***	0.0573	0.155**	0.00610	0.150***	0.0226	0.144*	0.0448	0.103	0.124
	(0.0425)	(0.0597)	(0.0651)	(0.0614)	(0.0498)	(0.0526)	(0.0835)	(0.0951)	(0.0977)	(0.120)
Some College	0.101	0.195**	0.146***	0.155**	0.0988	0.0797	0.199***	0.146	0.236**	0.170
	(0.0685)	(0.0766)	(0.0508)	(0.0704)	(0.0706)	(0.0657)	(0.0724)	(0.110)	(0.114)	(0.151)
College and above	0.302***	0.220*	0.370***	0.489***	0.195*	0.166*	0.293**	0.312***	0.459***	0.398**
	(0.114)	(0.122)	(0.136)	(0.0636)	(0.107)	(0.0917)	(0.133)	(0.0761)	(0.122)	(0.165)
Recall	0.146	0.167	0.190	0.0756	0.208	0.290**	0.152	0.192	0.113	0.0587
	(0.102)	(0.159)	(0.150)	(0.202)	(0.199)	(0.118)	(0.203)	(0.250)	(0.228)	(0.212)
Weeks left	0.000772	0.00748*	0.00567	0.00383	0.00439	0.00804***	0.00825***	0.00583	0.0121***	0.0110**
	(0.00470)	(0.00430)	(0.00428)	(0.00312)	(0.00480)	(0.00309)	(0.00191)	(0.00414)	(0.00456)	(0.00515)
Black	-0.298***	-0.311***	-0.255***	-0.295***	-0.234**	-0.300***	-0.286**	-0.185*	-0.312***	-0.361***
	(0.0871)	(0.0925)	(0.0883)	(0.0533)	(0.0958)	(0.0756)	(0.119)	(0.0987)	(0.0299)	(0.124)
Hispanic	-0.159*	-0.187*	-0.0889	-0.0868	-0.272***	-0.136	-0.107***	0.0306	-0.266**	-0.151*
	(0.0921)	(0.0996)	(0.116)	(0.0736)	(0.0585)	(0.110)	(0.0230)	(0.0945)	(0.121)	(0.0890)
Asian	-0.0495	-0.405	0.0686	-0.214	-0.246	-0.147	0.0151	-0.611***	-0.475	0.374
	(0.345)	(0.316)	(0.249)	(0.279)	(0.250)	(0.234)	(0.428)	(0.174)	(0.327)	(0.436)
Indian	-0.176	-0.00182	-0.0434	-0.0186	-0.216	-0.0566	0.0771	0.0853	0.238	-0.0272
	(0.236)	(0.0662)	(0.135)	(0.0768)	(0.148)	(0.114)	(0.243)	(0.197)	(0.236)	(0.272)
Observations	5541	5466	5484	5455	5455	5491	5483	5457	5481	5406
Log lik.	-2452.2	-2259.2	-2121.7	-2147.2	-2017.6	-1986.7	-1953.1	-1902.0	-1762.5	-1385.6

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B. Appendix: Regression Kink Design

In several cases, the study of UIB relies on the use of the regression kink design (RKD) (see, e.g., Card et al. (2015), Card et al. (2015), Landais (2015)). The intuition behind this approach rests on the formulaic relationship between UIB and HQ, according to which $UIB \equiv f(HQ) = b\min(HQ, M)$, with b the replacement rate and bM the maximum level of UIB allowed for in a given state and year. Assuming that benefit recipients are not able to precisely manipulate their HQ to systematically place themselves below (or above) the cutoff bM, and that recipients near the cutoff are comparable, one can identify the *local* average causal treatment effect *at the threshold* $HQ = bM$:

$$\tau = \frac{\lim_{h_0 \to bM^+} \left. \frac{dP(S=1|HQ=h)}{dh} \right|_{h=h_0} - \lim_{h_0 \to bM^-} \left. \frac{dP(S=1|HQ=h)}{dh} \right|_{h=h_0}}{\lim_{h_0 \to bM^+} \left. \frac{df(h)}{dh} \right|_{h=h_0} - \lim_{h_0 \to bM^-} \left. \frac{df(h)}{dh} \right|_{h=h_0}}. \tag{B1}$$

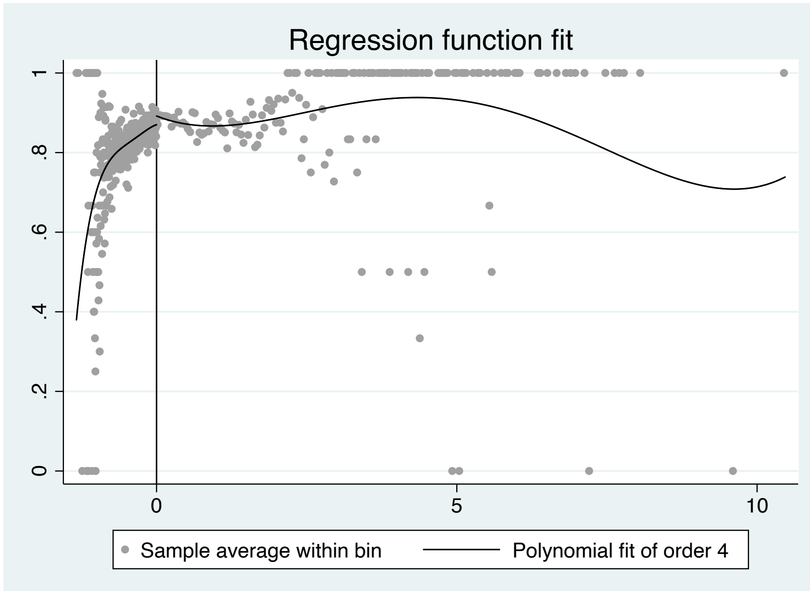
Intuitively, if UIB has a causal effect on search, given the kink in the deterministic relationship between HQ and UIB, there should be a kink in the relationship between search and HQ at M. One can therefore use data *local to the kink* to learn the effect of UIB on search for people whose HQ are close to the threshold bM. In practice, the effect is estimated through a local polynomial regression that uses data around the kink.

We implement our RKD analysis first graphically, using the Stata package Calonico, Cattaneo and Titiunik (2014*a*), which implements the methods put forward by Calonico, Cattaneo and Titiunik (2014*b*). We use Calonico, Cattaneo and Titiunik (2014*a*) default choices of tuning parameters. In Figure B1 we show that in our data there is graphical evidence for a kinked relationship between search and HQ at M: as the figure shows, to the left of the kink the probability of search grows rapidly with HQ, while to the right of the kink it is much flatter.[40]

Using Calonico, Cattaneo and Titiunik (2014*a*) Stata package, we determine the bandwidth to be used in estimating the effect of interest (which equals 0.209 in our data). We then estimate the effect of UIB on search using a specification similar to Massenkoff (2020). Because benefit schedules vary across states and years, we include in the RKD specification cell fixed effects (denoted by $\alpha_{z,t}$ where z is the state and t is the year) for each unique combination of state, replacement rate, and benefit maximum. To allow for the possibility that not all claimants may receive the exact benefit predicted by their schedule, we use the fuzzy RKD method (Card et al., 2015, Section 2.2.2). We implement the method through two stage least squares for the subsample with $|HQ - M| < 0.209$,

[40] The binned data show a similar pattern.

Figure B1: RKD Plot of Search on HQ



Notes: Data normalized so that $M = 0$.

where the first and second stage specifications are, respectively,

$$UIB_{i,z,t} = \gamma z, t + \gamma \mathbf{1}(HQ_{i,z,t} > M) + \sum_{p=1}^{\bar{p}} [\nu_p (HQ_{i,z,t} - M)^p + \eta_p \mathbf{1}(HQ_{i,z,t} > M)(HQ_{i,z,t} - M)^p] + r_{i,z,t}, \tag{B2}$$

$$S_{i,z,t} = \alpha_{z,t} + \alpha_0 \mathbf{1}(HQ_{i,z,t} > M) + \tau UIB_{i,z,t} + \sum_{p=1}^{\bar{p}} \delta_p (HQ_{i,z,t} - M)^p + \epsilon_{i,z,t}. \tag{B3}$$

The results for the case $\bar{p} = 1$ are in Table B1. While the effect of UIB on search is positive, it is very imprecisely estimated: the confidence intervals are wide and cover zero.[41]

Our RKD results here are related to the recent work of Massenkoff (2020) who uses a RKD approach and data from the BAM, to study the effect of UIB on different variables than ours: the unemployment duration, the log reservation wage, the reservation ratio, an indicator for switching occupations, and the number of contacts for the benefits recipient. In each case, similar to our RKD results, Massenkoff (2020) RKD results suggest no obvious response to UIB.

Overall, the imprecision in our RKD estimates is unsurprising, due to the slow rate of convergence of nonparametric estimators of derivatives (see, e.g. Li and Racine, 2007). Indeed, Card et al. (2015) obtain results on the effect of unemployment benefits on unemployment duration in Aus-

[41] As expected, this is not ameliorated by increasing the value of $\bar{p}$: the confidence intervals get wider and the sign of UIB becomes negative.

Table B1: Fuzzy RKD Estimates

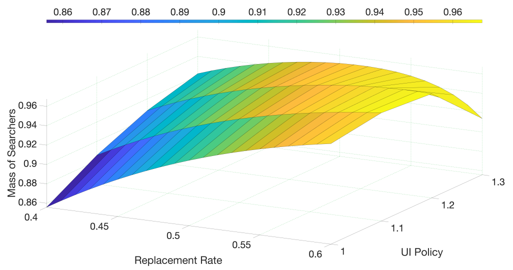
	First Stage			
Variable	Estimate	Std. Err.	t-stat	95% Confidence Interval
$\mathbf{1}(HQ > M)$	0.001474	0.0004125	3.57	(0.0006655, 0.0022825)
$HQ - M$	0.1545972	0.0023233	66.54	(0.1500433, 0.1591511)
$\mathbf{1}(HQ > M)(HQ - M)$	-0.1424429	0.0035186	-40.48	(-0.1493397, -0.1355461)
	Second Stage			
Variable	Estimate	Std. Err.	t-stat	95% Confidence Interval
UIB	0.3159402	0.5617932	0.56	(-0.7852247, 1.417105)
$\mathbf{1}(HQ > M)$	-0.0029539	0.0093536	-0.32	(-0.0212878, 0.01538)
$HQ - M$	0.0969831	0.0655485	1.48	(-0.0314978, 0.225464)

tria that are indicative of a positive elasticity, but that are imprecisely estimated with confidence intervals that cover zero when using RKD methods.

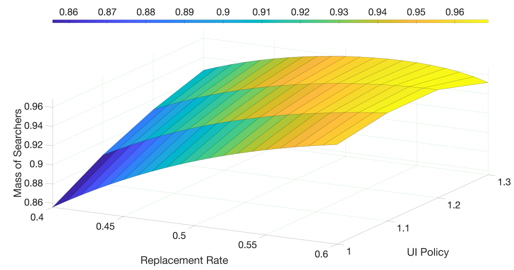
Finally, we note again that in our main empirical analysis in Section 2 we use plausibly exogenous variation in UIB. Unlike the RKD approach that uses solely local to the kink observations, our approach in Section 2 leverages the *entirety* of the wage distribution.

C. Appendix: UI Reforms Without Clearing the Government Budget Constraint

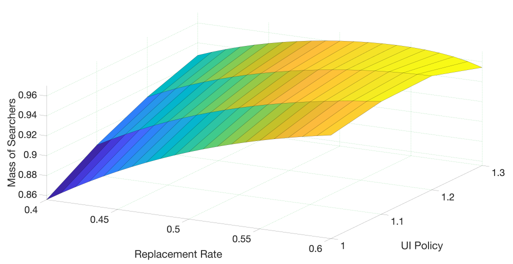
Figure C1: Relation between UI Benefits and Fraction of Searchers



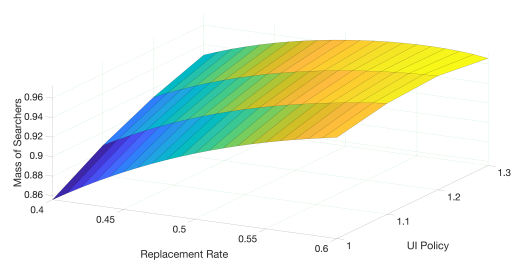
(a) Nash Wages: Govt. Clearing



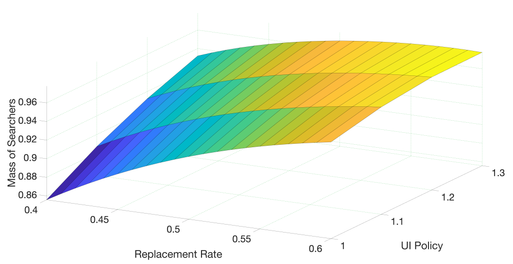
(b) Nash Wages: Constant Tax Rate



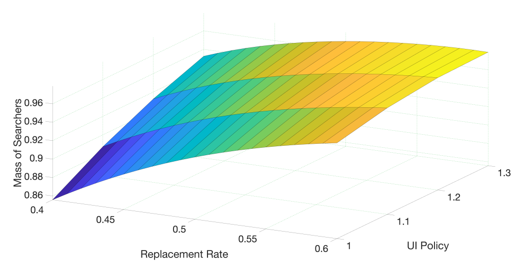
(c) Semi-Flexible Wages: Govt. Clearing



(d) Semi-Flexible Wages: Constant Tax Rate

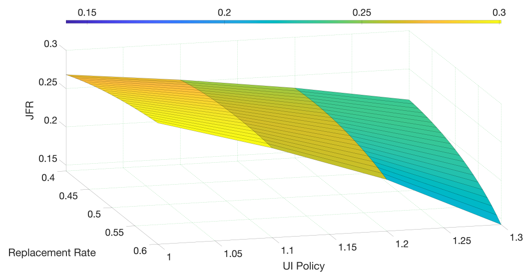


(e) Sticky Wages: Govt. Clearing

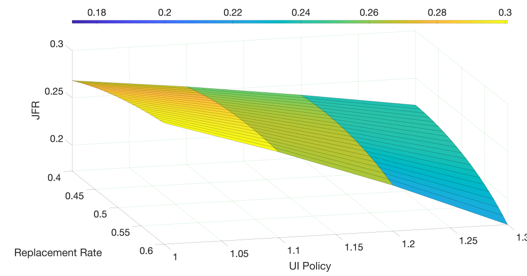


(f) Sticky Wages: Constant Tax Rate

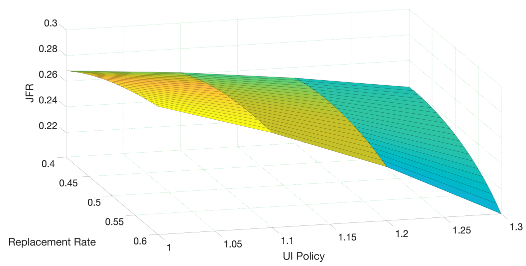
Figure C2: Relation between UI Benefits and Job-Finding Probability



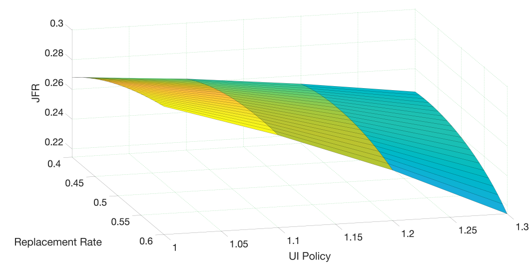
(a) Nash Wages: Govt. Clearing



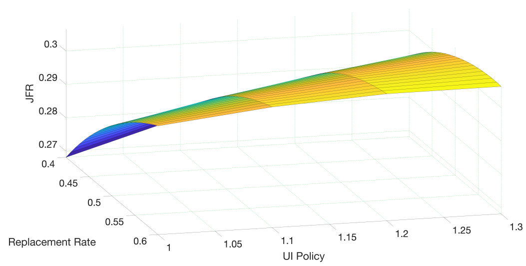
(b) Nash Wages: Constant Tax Rate



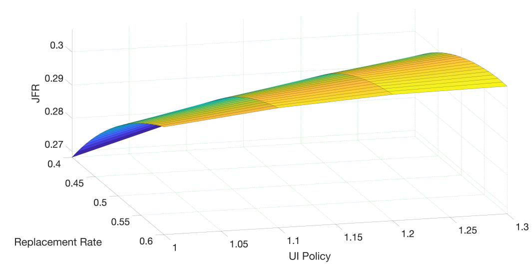
(c) Semi-Flexible Wages: Govt. Clearing



(d) Semi-Flexible Wages: Constant Tax Rate

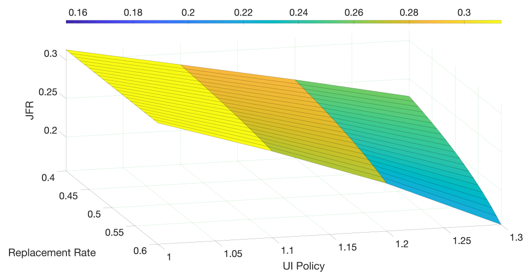


(e) Sticky Wages: Govt. Clearing

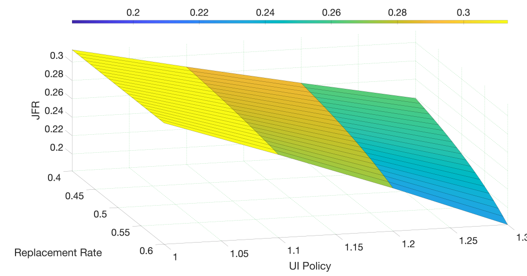


(f) Sticky Wages: Constant Tax Rate

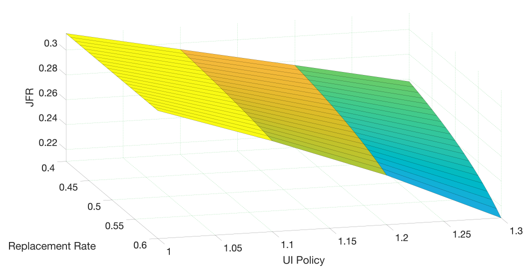
Figure C3: Relation between UI Benefits and Job-Finding Probability (Conditional on Searching)



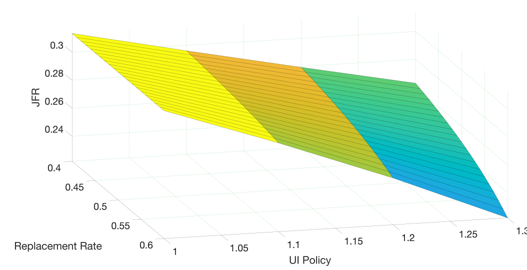
(a) Nash Wages: Govt. Clearing



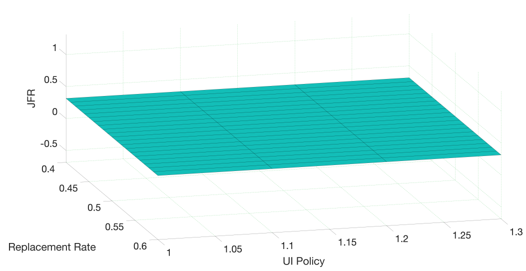
(b) Nash Wages: Constant Tax Rate



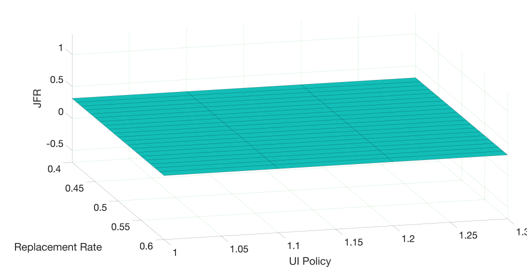
(c) Semi-Flexible Wages: Govt. Clearing



(d) Semi-Flexible Wages: Constant Tax Rate

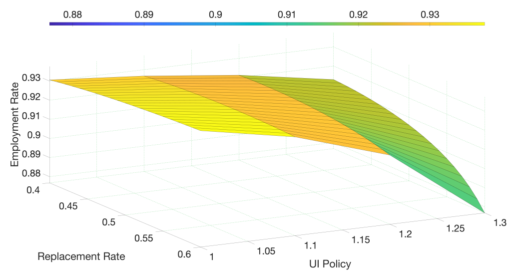


(e) Sticky Wages: Govt. Clearing

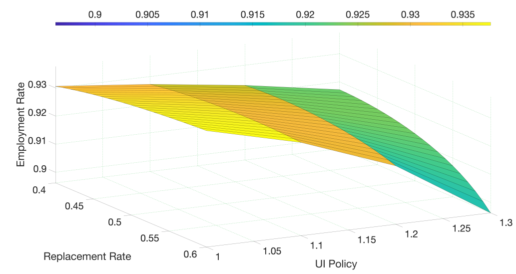


(f) Sticky Wages: Constant Tax Rate

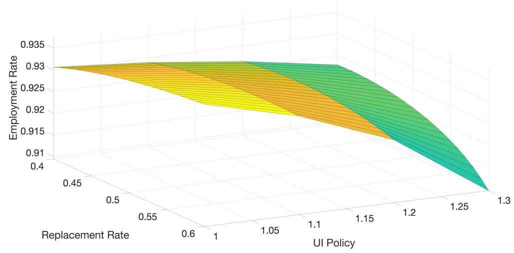
Figure C4: Relation between UI Benefits and Employment Rate



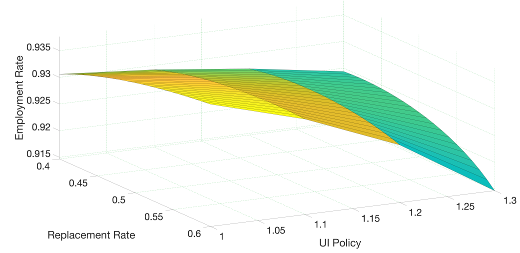
(a) Nash Wages: Govt. Clearing



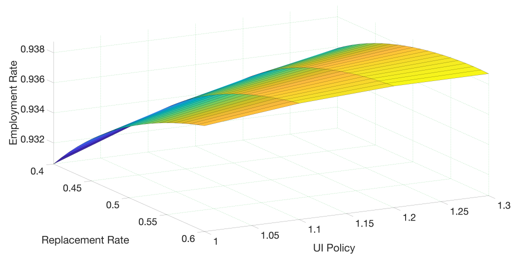
(b) Nash Wages: Constant Tax Rate



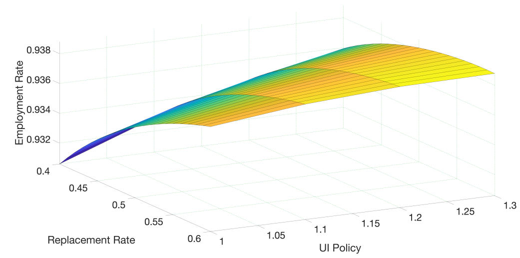
(c) Semi-Flexible Wages: Govt. Clearing



(d) Semi-Flexible Wages: Constant Tax Rate

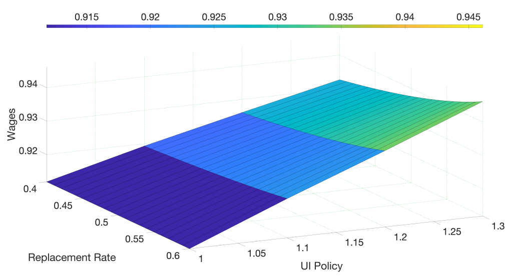


(e) Sticky Wages: Govt. Clearing

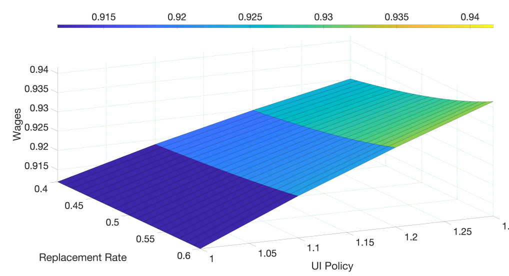


(f) Sticky Wages: Constant Tax Rate

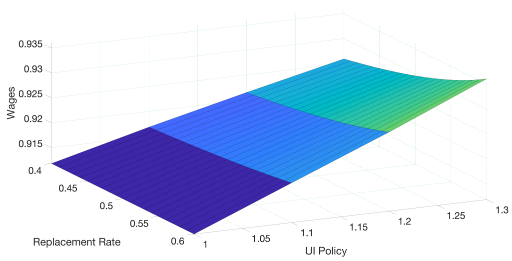
Figure C5: Relation between UI Benefits and Wages



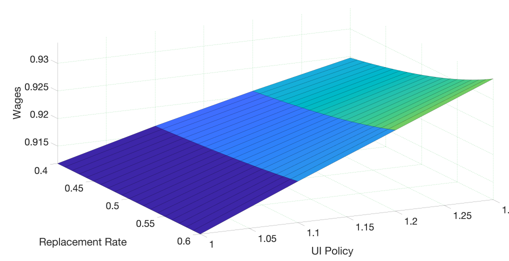
(a) Nash Wages: Govt. Clearing



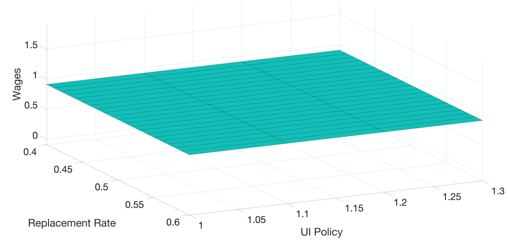
(b) Nash Wages: Constant Tax Rate



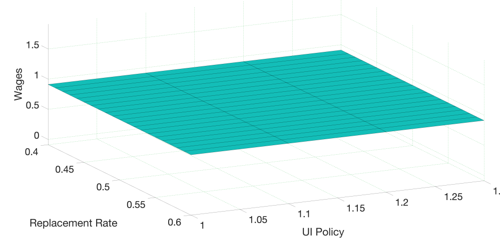
(c) Semi-Flexible Wages: Govt. Clearing



(d) Semi-Flexible Wages: Constant Tax Rate



(e) Sticky Wages: Govt. Clearing



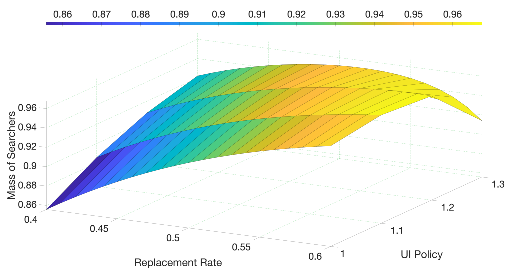
(f) Sticky Wages: Constant Tax Rate

D. Appendix: Model with One Value of the Bargaining Weight

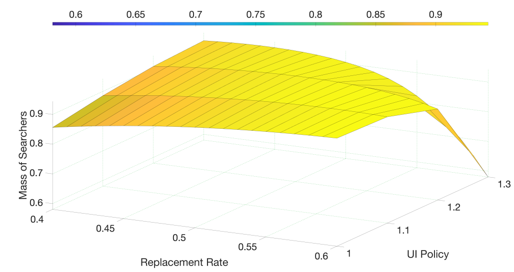
The figures in this appendix show the results for our benchmark economy when the bargaining weight parameter ρ is calibrated to be identical across all values of the replacement rate vector $\vec{b}$. In the benchmark model, to generate the same value of the job-finding rate across the different values of $\vec{b}$, our calibration yields values of ρ that are decreasing in b. Since in this version of the model ρ is the same, then under the Nash-bargaining wage scenario, the sensitivity of the job-finding rate to a change in the UIB is higher, resulting in a bigger fall in the job-finding rate and the employment rate. As in our main model, the "semi-flexible" wages case lies in between the

Nash bargaining model and the sticky wages model. Overall, the results of this specification are similar to our main specification.

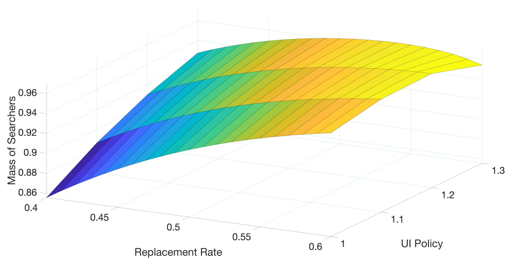
Figure D1: Relation between UI Benefits and Fraction of Searchers



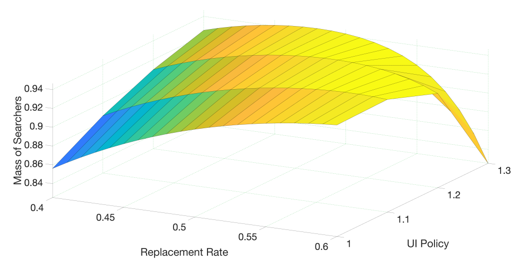
(a) Nash Wages: Benchmark Economy



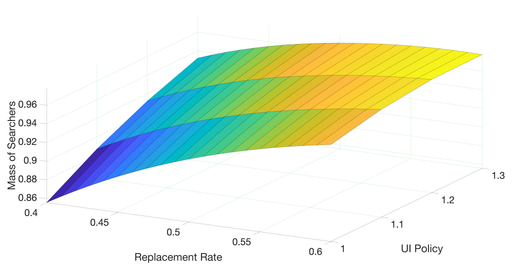
(b) Nash Wages: Alternative Bargaining



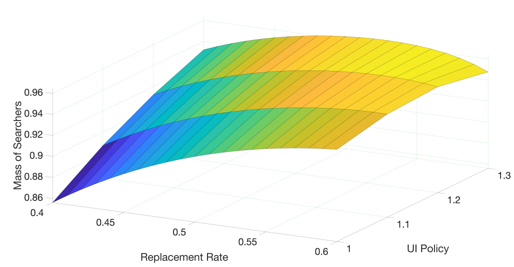
(c) Semi-Flexible Wages: Benchmark Economy



(d) Semi-Flexible Wages: Alternative Bargaining

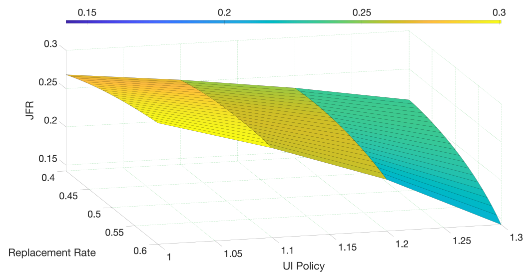


(e) Sticky Wages: Benchmark Economy

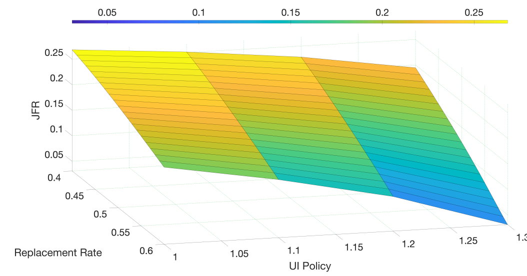


(f) Sticky Wages: Alternative Bargaining

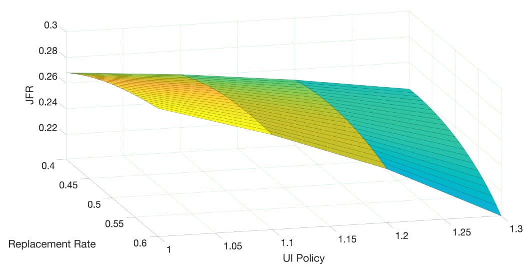
Figure D2: Relation between UI Benefits and Job-Finding Probability



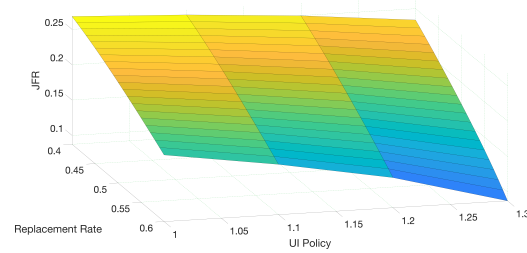
(a) Nash Wages: Benchmark Economy



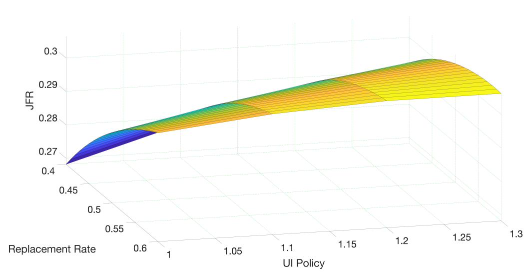
(b) Nash Wages: Alternative Bargaining



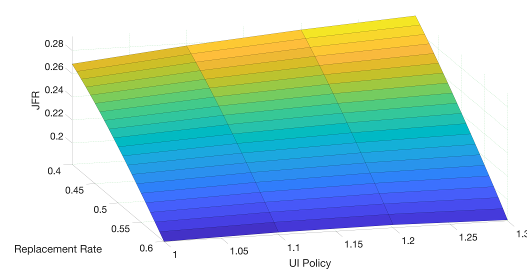
(c) Semi-Flexible Wages: Benchmark Economy



(d) Semi-Flexible Wages: Alternative Bargaining

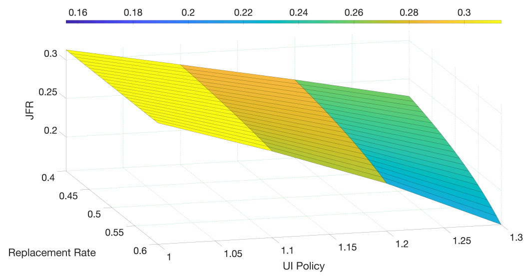


(e) Sticky Wages: Benchmark Economy

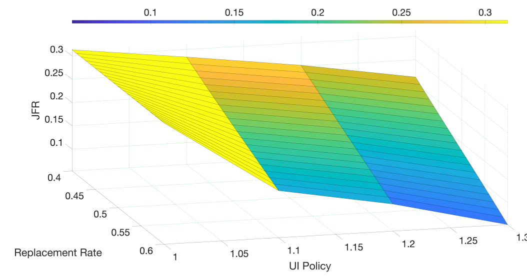


(f) Sticky Wages: Alternative Bargaining

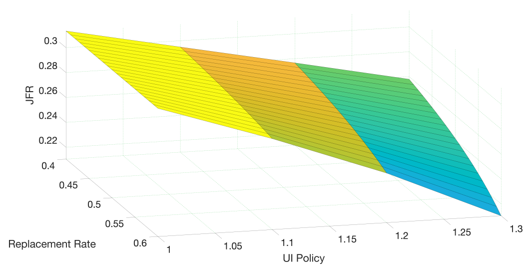
Figure D3: Relation between UI Benefits and Job-Finding Probability (Conditional on Searching)



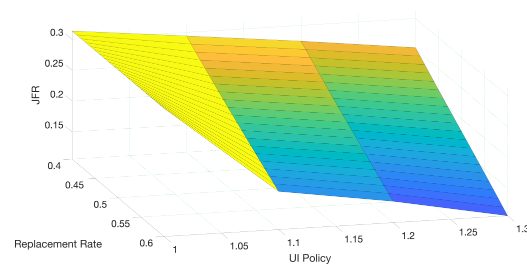
(a) Nash Wages: Benchmark Economy



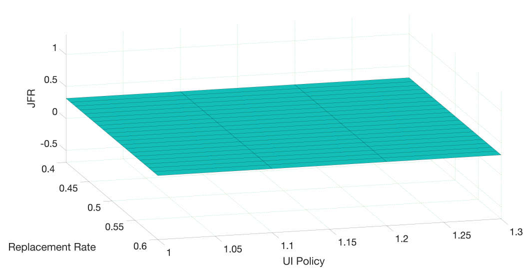
(b) Nash Wages: Alternative Bargaining



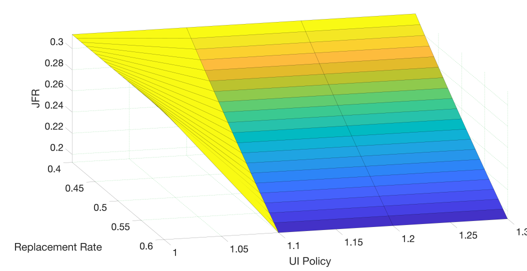
(c) Semi-Flexible Wages: Benchmark Economy



(d) Semi-Flexible Wages: Alternative Bargaining

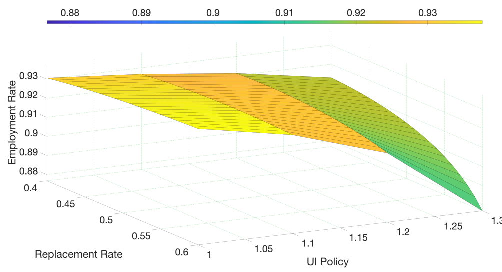


(e) Sticky Wages: Benchmark Economy

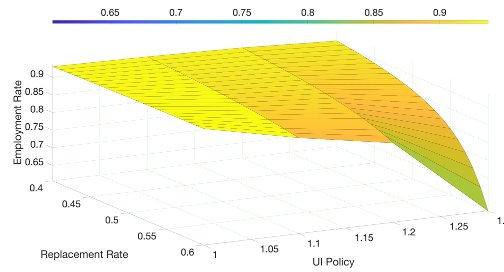


(f) Sticky Wages: Alternative Bargaining

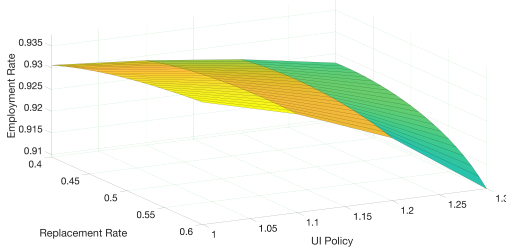
Figure D4: Relation between UI Benefits and Employment Rate



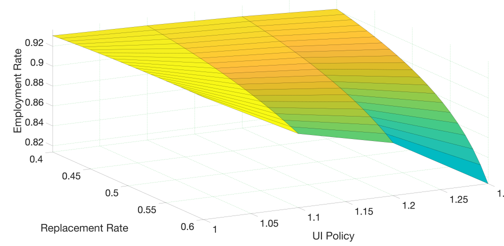
(a) Nash Wages: Benchmark Economy



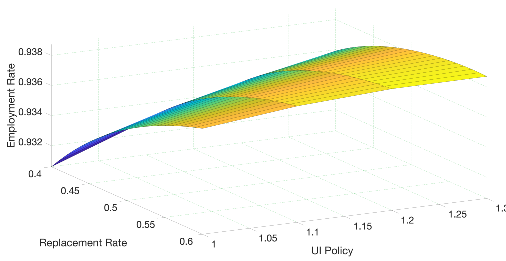
(b) Nash Wages: Alternative Bargaining



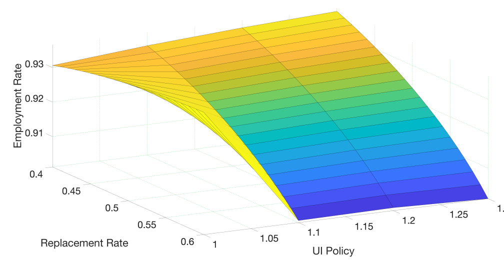
(c) Semi-Flexible Wages: Benchmark Economy



(d) Semi-Flexible Wages: Alternative Bargaining

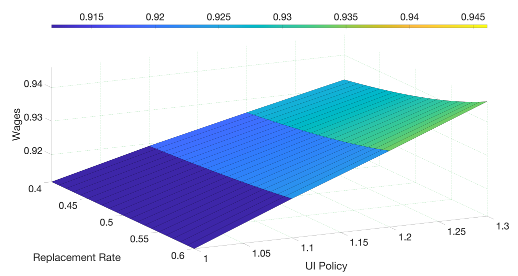


(e) Sticky Wages: Benchmark Economy

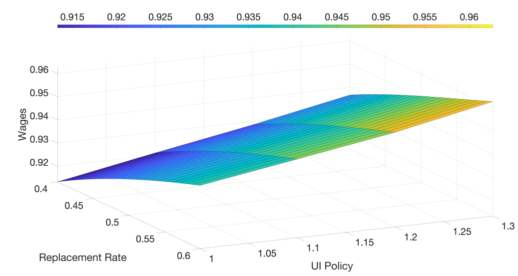


(f) Sticky Wages: Alternative Bargaining

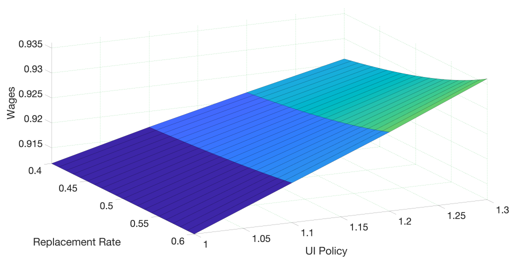
Figure D5: Relation between UI Benefits and Wages



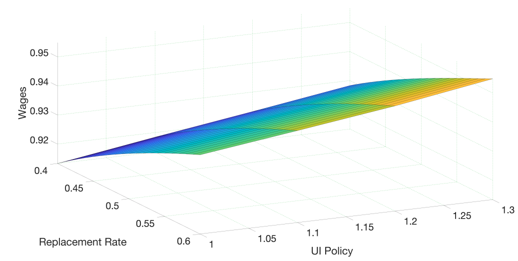
(a) Nash Wages: Benchmark Economy



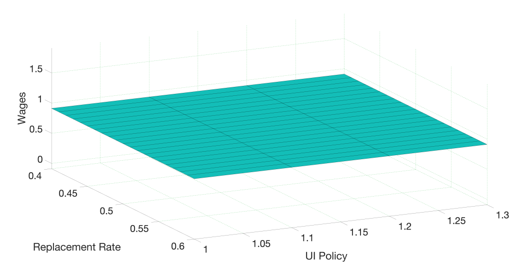
(b) Nash Wages: Alternative Bargaining



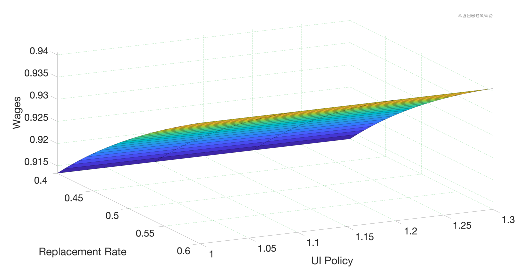
(c) Semi-Flexible Wages: Benchmark Economy



(d) Semi-Flexible Wages: Alternative Bargaining



(e) Sticky Wages: Benchmark Economy



(f) Sticky Wages: Alternative Bargaining

E. Appendix: Model with Contractible Search Costs

In this appendix, we present an alternative model economy where, in contrast to the benchmark model, search costs are *contractible*. In this variant of the model, wages vary among individuals based on their replacement rates as well as the monetary search cost they incur. Preferences, budget constraints, production, and meeting technologies are the same as in the benchmark model.

E.1. Environment

Heterogeneity Individuals are heterogeneous along two dimensions. First, they differ in terms of their cost of searching. Specifically, the monetary cost of search $s \geq 0$ is i.i.d. and drawn from a Log-Normal distribution with mean μ_s and variance σ_s^2. Once the individual gets her initial draw, the value of s stays the same forever. Second, as in the benchmark model, individuals differ in terms of their replacement rates, $b \in [b_{\min}, b_{\max}]$, defined as the ratio of UIB to wages.

Market structure To keep things simple, we assume that labor markets are segmented by replacement rates b and the search cost s. Firms post vacancies in the submarket with the highest expected payoff, knowing with certainty the value of the replacement rate b that the unemployed carry in that submarket, as well as the search cost s that the unemployed would incur if she chooses to search. The mass of firms in each submarket is determined in free-entry equilibrium, independently of other submarkets.

The labor market is organized in a continuum of submarkets indexed by the couple (b,s). In each submarket, matching is subject to a search friction. The ratio of vacancies to searchers $\theta(b,s)$ denotes tightness of submarket (b,s). We denote the probability that an individual meets a vacancy by $p(\theta(b,s))$, where $p : \mathbb{R}_+ \rightarrow [0,1]$ is a strictly increasing function with $p(0) = 0$. And the rate at which a vacancy meets a searcher by $q(\theta(b,s)) = p(\theta(b,s))/\theta(b,s)$.

E.2. Value Functions

Individual's problem In each submarket (b,s), individuals can be in three different labor-market states: (i) employed (e), (ii) unemployed and searching (u), (iii) unemployed and not-searching (n).

The value of being employed V_e in submarket (b,s) is

$$V_e(b,s) = u(c_e) + \beta\left[\delta \max\left\{V_u(b,s), V_n(b,s)\right\} + (1-\delta)V_e(b,s)\right], \tag{E1}$$

where $c_e = (1-\tau)w(b,s)$ is consumption if employed and $w(b,s)$ is the wage rate whose determination we describe below. The parameter $\delta \in [0,1]$ is an exogenous and constant job destruction rate, which is the same in all submarkets.

The value of being unemployed and searching, V_u, and the value of being unemployed and not-searching, V_n, in submarket (b,s) are, respectively,

$$V_u(b,s) = u(c_u) + \beta \{ p(\theta(b,s)) V_e(b,s) + [1 - p(\theta(b,s))] \max \{ V_u(b,s), V_n(b,s) \} \}, \tag{E2}$$
$$V_n(b,s) = u(c_n) + \beta V_n(b,s), \tag{E3}$$

where $c_u = bw(b,s) - s$ and $c_n = bw(b,s)$ are consumption if searching and not-searching, respectively.

Firm's problem Vacancies can be either filled, so that a job is created, or unfilled. The value of a job J in submarket (b,s) is

$$J(b,s) = \epsilon - w(b,s) + \beta [\delta V + (1 - \delta) J(b,s)], \tag{E4}$$

where ϵ is the output of a match, which is the same in all submarkets, and V is the value of posting a vacancy.

In an equilibrium with free entry, the value of an unfilled vacancy is zero at all times, and in all submarkets, which gives that the expected cost of posting a vacancy equals the discounted value of a job,

$$\frac{k}{q(\theta(b,s))} = \beta J(b,s), \tag{E5}$$

where $k \geq 0$ is the unit cost of posting and maintaining a vacancy.

E.3. Nash Bargaining

When a searcher and a firm meet, they enter into bilateral Nash-bargaining. Search costs are contractible. Here, in contrast to the benchmark model, the worker's forgone value of accepting a job offer is $V_u(b,s)$, which depends on the search cost s through consumption $c_u = bw(b,s) - s$. As standard, we assume that bargaining resumes every period and that the wage is determined according to

$$w^{\text{Nash}}(b,s) = \arg\max \, [V_e(b,s) - V_u(b,s)]^{\rho} \, J(b,s)^{1-\rho}, \tag{E6}$$

where $\rho \in [0,1]$ is a parameter capturing the individuals' bargaining weight.

The solution to the Nash-bargaining problem yields a modified sharing rule,

$$(1 - \tau) \rho u_c(c_e) J(b,s) = (1 - \rho) [V_e(b,s) - V_u(b,s)], \tag{E7}$$

which implies that the wage is generally a function of the replacement rate b, and of the search cost s. We expand more on this below.

E.4. Equilibrium

As in the standard DMP model, as well as in our benchmark model, the equilibrium is block-recursive. That is, we can solve for the wages and tightness ratios independently of the stocks of employment, unemployment, and the mass of searchers. Equipped with wages and tightness ratios, we can then calculate search cutoffs $s^*(b)$ and so the mass of searchers $G(s^*(b))$ in each submarket.

Market tightness and wages In each submarket, the free-entry condition (E5) determines the market tightness ratio given the wage,

$$\frac{k}{q(\theta(b,s))} = \frac{\beta\left[\epsilon - w(b,s)\right]}{1-\beta(1-\delta)}. \tag{E8}$$

Then, the sharing rule (E7) determines the wage given the tightness ratio,

$$(1-\tau)\rho u_c(c_e) \times \frac{k}{\beta q\left(\theta(b,s)\right)} = \frac{(1-\rho)\left[u\left(c_e\right) - u\left(c_u\right)\right]}{1-\beta\left[1-\delta-p(\theta(b,s))\right]}, \tag{E9}$$

where $c_e = (1-\tau)w(b,s)$, $c_u = bw(b,s) - s$, and τ is here the tax rate that balances the government budget.

Linear utility case To provide some intuition, it is useful to consider the case in which the utility function is linear in consumption, such that $u(c) = c$ and $u_c(c) = 1$. In the linear utility case, and setting $\tau = 0$, equation (E9) simplifies to

$$\frac{\rho k}{\beta q\left(\theta(b,s)\right)} = \frac{(1-\rho)\left[(1-b)\,w(b,s) + s\right]}{1-\beta\left[1-\delta-p(\theta(b,s))\right]}. \tag{E10}$$

First, equation (E8) gives a downward-sloping quasi-labor demand curve. The higher the wage, the higher the job-filling probability, which implies a lower tightness ratio. Second, equation (E10) gives an upward-sloping quasi-labor supply curve. The higher the wage, the higher the tightness ratio. Intuitively, a higher tightness ratio implies a lower expected unemployment duration, which strengthens the bargaining position of the unemployed at the expense of the firm. The intersection of these two curves gives the equilibrium wage and tightness ratio in each submarket.

The comparative statics with respect to the replacement rate is unambiguous. As b does not enter equation (E8), it necessarily affects the equilibrium solely through equation (E10). Everything else equal, a higher b induces a new equilibrium with a higher wage and a lower tightness ratio. A higher replacement rate makes the individual's bargaining position stronger leading to a higher bargained wage and thereby diminished incentive to post vacancies.

Note also that the search cost s does not enter equation (E8), but it enters equation (E10) as a left-ward shifter of the quasi-labor supply curve. Everything else equal, a higher value of the search cost induces an equilibrium with a lower wage and a higher tightness ratio. The intuition for this result is fairly simple. When the unemployed individual enters the bargaining with the firm, the search cost is *sunk*. This weakens the bargaining position of the unemployed, giving an advantage to the firm which lowers the wage. From the free-entry condition, a lower wage mandates a higher tightness ratio, and so a higher probability to find a job.

Search cutoff In each submarket (b, s), the search decision satisfies a reservation policy rule such that if $V_u > V_n$ the individual searches, otherwise, if $V_u \leq V_n$, he or she does not search. The indifference condition $V_u = V_n$ implies then a cutoff value s^*, such that is $s < s^*$ the individual searches, whereas if $s \geq s^*$ the individual does not search. Note that the cutoff value s^* depends on b. Notably, the higher b, the higher the cutoff s^* that makes the individual indifferent between searching and not searching. Formally, the search cutoff is implicitly determined by

$$\frac{(1-\beta(1-\delta))u(c_u) + \beta p(\theta(b,s))u(c_e)}{1-\beta(1-\delta)+\beta p(\theta(b,s))} = u(c_n). \tag{E11}$$

In this model, one cannot formally show that there is a unique cutoff of search cost per value of replacement ratio. However, quantitative evaluation of the model suggests that the mapping between b and s is indeed unique and monotonically increasing, as in the benchmark model.[42]

[42]Results are available upon request from the authors.